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Modelling land use and land cover change on the Mongolian Plateau

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Abstract

Changes in land use and land cover significantly alter the Earth's energy balance and biogeochemical cycles, which contributes to climate change and — in turn — affects land surface properties and the provision of ecosystem services. The dramatic land use and land cover change in arid and semi-arid regions of Inner Mongolia, China, have led to vast land degradation, especially grassland degradation. Most degradation, however, is caused by increasingly intensive human disturbance, such as overgrazing and rapid urbanisation. In around 2000, the Chinese government launched a set of ecological protection policies aimed at protecting vulnerable grassland ecosystems and improving human livelihoods. The year 2000 marked a turning point in degradation.

The aims of this thesis are to gain an integrated and systematic understanding of the processes and determinants of land degradation on the Mongolian Plateau. Xilingol was chosen as a suitable example, mainly since it is covered by vast grassland, and has experienced almost all ecological policies that have been implemented in China. Two distinct phases were identified in this region: 1975-2000 and 2000-2015. During the first phase (up to 2000), land degradation was the dominant land use change process, accounting for 11.4% of the total area. During this phase, human disturbance was the major driver in eight counties, whereas the water condition was the dominant driver in six counties. During the second phase (post-2000), land restoration increased (12.0% of the total area), whereas degradation continued, resulting in a further 9.5% of degraded land. During this phase, urbanisation became the dominant driver of land degradation in seven counties, while effects resulting from human disturbance and water availability decreased after 2000.

After identifying the major drivers of degradation, the complex relationships between drivers and grassland degradation were captured. Likewise, the primary drivers of grassland degradation and the high risk of further degraded regions were mapped. The results indicated that the distance to dense, moderately dense grass and sparse grass and sheep density were responsible for the grassland degradation dynamics. In particular, the complex interaction between land use change processes, policy change and driver dynamics were highlighted.

In this thesis, a clustering method, partial order theory and Hasse diagram techniques were first used to identify the major drivers of land degradation at the county level. Subsequently, an approach from machine learning, XGBoost (eXtreme Gradient Boosting), was used to predict the dynamics of grassland degradation. Moreover, SHAP (SHapley Additive exPlanations) values were used to open up the black box model, and the primary driver was extracted for each pixel showing degradation. The results revealed that land use change and land degradation were seriously affected by different regional drivers on the Inner Mongolian plateau. This thesis delivers new insights into land use change and its drivers on the Mongolian Plateau using different methods, and improves the state of technology and methodology in identifying drivers of land use change.

Keywords: Land use change, Mongolian Plateau, Partial order theory, Machine learning, Land use model

Zusammenfassung

Veränderungen der Landnutzung und der Landbedeckung verändern die Energiebilanz der Erde und ihre biogeochemischen Zyklen, was zum Klimawandel beiträgt und wiederum die Landoberflächeneigenschaften und die Gewährleistung von Ökosystemleistungen beeinflusst. Der dramatische Landnutzungs- und Landbedeckungswandel in der ariden und semiariden Region der Inneren Mongolei, China, haben zu einer erheblichen Landdegradation beigetragen, insbesondere in der als Grünland genutzten Steppe. Der Hauptanteil der Degradation ist auf mehr oder weniger intensive menschliche Einflussnahme zurückzuführen, wie die Überweidung der Steppe und die schnell voranschreitende Städtebildung. Um das Jahr 2000 herum veranlasste die chinesische Regierung ein Bündel von Umweltschutz-Richtlinien, die das sensible Steppen-Ökosystem schützen und das Leben der Einwohner verbessern helfen sollten. Das Jahr 2000 markierte einen Wendepunkt hinsichtlich der Land degradation.

Ziel dieser Arbeit ist es, ein integriertes und systematisches Verständnis der Prozesse und Einflussfaktoren der Landdegradation auf der Mongolischen Hochebene zu gewinnen. Der Bezirk Xilingol in der Inneren Mongolei, China, wurde als geeignetes Beispiel ausgewählt, weil es zu einem großen Flächenanteil von Grassteppe bedeckt ist und fast alle Phasen der Umweltpolitik Chinas durchlaufen hat. Es wurden zwei deutlich voneinander abgrenzbare Phasen identifiziert, von 1975 bis 2000 und von 2000 bis 2015. Während der ersten Phase, bis 2000, war Landdegradation der dominante Landnutzungswandelprozess, der 11.4 % der Gesamtfläche betraf. In dieser Phase war die menschliche Einflussnahme der Hauptfaktor in acht Landkreisen, die sich ändernden Wasserverhältnisse war es in sechs Landkreisen. Während der zweiten Phase, ab 2000, setzte ein spürbare Erholung des Zustandes auf 12 % des Gesamtgebietes ein, während die Degradation jedoch weiter voranschritt und zusätzliche 9,5 % des Landes veränderte. Während dieser Phase wurde die Städtebildung zum dominanten Treiber für die Landdegradierung in sieben Landkreisen, während der Einfluss menschlicher Störungen und der Wasserverfügbarkeit wieder zurückging.

Nach der Identifizierung der Haupttreiber für die Landdegradation, wurde die komplexe Beziehung zwischen verschiedenen Treibern und der Grassteppen-Degradation untersucht. So wurden die Haupttreiber für die aktuelle Grassteppen-Degradation und die Risiken für zukünftige Degradation in der Region kartiert. Die Ergebnisse zeigten, dass die Beziehung zwischen dicht bedeckter, moderat bedeckter, und spärlich bedeckter Grassteppe und die Dichte des Schafbesatzes für die Degradationsdynamik in der Grassteppe verantwortlich waren. Auch steht die Region, die durch eine gute Qualität des Grases gekennzeichnet ist, unter einem hohen Risiko zukünftiger Degradierung. Insbesondere wurde die komplexe Interaktion zwischen den Veränderungen der Landnutzung, den Veränderung der Politik-Strategien und der Treiberdynamik dargestellt.

In dieser Arbeit wurden die Methoden der Clusteranalyse, der Partial-Order-Theorie, und der Hasse Diagramme eingesetzt, um die Haupttreiber der Landdegradation auf Landkreisebene zu identifizieren.

Dann wurde ein Ansatz aus dem maschinellen Lernen, XGBoost (eXtreme Gradient Boosting) verwendet, um die Dynamik der Grassteppen-Degradation vorauszusagen. Darüber hinaus wurde SHAP (SHapley Additive exPlanations) eingesetzt, um das von XGBoost erstellte Black-Box-Modell zu in seine Bestanteile zu zerlegen und für jedes Degradations-Pixel in der Karte den Haupttreiber zu extrahieren.

Die Ergebnisse zeigen, dass Landnutzungswandel und damit die Landdegradation auf der Innermongolischen Hochebene stark von mehreren, regional unterschiedlichen Treibern beeinflusst wurden.

Diese Arbeit hat dazu beigetragen, die Wissenslücke hinsichtlich eines umfassenden Verständnisses der Landnutzungsänderungen und seiner Treiber auf der mongolischen Hochebene zu verringern und die Methoden und Technologien zur Identifizierung von Treibern des Landnutzungswandels zu verbessern.

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Chapter I:
Introduction

1 Research background

Land use and land cover represent an important part of ecological and geographical sciences, as well as other fields related to human-environment systems (Eric F. Lambin & Patrick Meyfroidt, 2011; Turner *et al.*, 1994; Verburg *et al.*, 2004, 2011). Land use and land cover are two related but different definitions. Land use refers to biophysical attributes of the Earth's surface, while land cover refers to the human purpose or intent applied to these attributes (Lambin *et al.*, 2001; Turner *et al.*, 1994). Cumulatively, land use and land cover change (LUCC) are major drivers of global environmental issues (Eric F. Lambin & Patrick Meyfroidt, 2011). Changes in land use and land cover considerably alter the Earth's energy balance and biogeochemical cycles, which contributes to climate change and in turn affects land surface properties and the provision of ecosystem services (Song *et al.*, 2018). They affect key aspects of Earth system functions, such as global biotic diversity and regional climate change, affecting ecological services that support human needs, which are also primary causes of land degradation (Lambin *et al.*, 2001). Human activities have undoubtedly contributed to most land use change on both a global and regional scale (Goldewijk, 2001; Lambin & Meyfroidt, 2011; Turner *et al.*, 1994). Today, about 60% of land use change is caused by human activities, and the remaining 40% by indirect drivers such as climate change (Song *et al.*, 2018). Deforestation, agricultural expansion, grassland degradation and urbanisation are the major components of global land use change.

1.1 Global land use change

Forests are crucial for the global water purification and carbon cycle; they also provide forest products and a number of ecological and environmental services, such as erosion control and the protection of biodiversity. The world's forests store an estimated 296 gigatonnes (Gt) of carbon in above-ground and below-ground biomass (FAO, 2016). Deforestation is the most rapid land use change in recent decades, and the primary cause of global environmental issues (Geist & Lambin, 2002). Forests covered about 50% of the Earth's land area 8,000 years ago, as opposed to 30% today (Lambin *et al.*, 2003). The Food and Agriculture Organization of the United Nations (FAO) estimated that there were 4,128 million hectares of forest (31.6% of global land area) in 1990, which had decreased to 3,999 million hectares (30.6%) by 2015; carbon stocks decreased by 11 Gt over the same period (FAO, 2016). Lambin et al. (2003) showed that the world's natural forests decreased by 16.1 million hectares per year on average in the 1990s, and that the net forest change rate was 9.6 million hectares per year from 1990-2000. Deforestation occurred most rapidly in tropical regions, especially in South America and Africa. As previous studies reported, population growth is the major driver of forest loss, but not the only one. In-migration is triggered by government policy to expand more settlements and to develop projects and extractive industries such as the timber industry. The underlying cause is that governments promote interest for specific groups through the exploration of natural resources, by securing territorial claims and national political support, to attract international capital and facilitate market opportunities (Lambin *et al.*, 2001). In recent years, many researchers have showed that forest area has exhibited a positive trend in recent years, especially in Asian countries (Chen *et al.*, 2019; FAO, 2016; Song *et al.*, 2018). The FAO (2016) reported that forest area has increased and that more than 50% of the total forest area is under a management plan. According to the FAO report, the forest annual net loss rate decreased from 0.18% to 0.08% (3.3 million hectares per year) between 2010 and 2015 (FAO, 2016). Forest degradation has been witnessed in several sub-regions. For example, China has launched a variety of policies to protect its forests, with the goal of mitigating land degradation, air pollution and climate change (Chen *et al.*, 2019). Song et al. (2018) also showed that tree canopy has increased by 35% in Europe, by 34% in China, and by 15% in the United States. Deforestation and reforestation have complex interactions with other land use change processes such as agricultural expansion.

Agricultural land currently accounts for approximately 38% of the global land. Agricultural expansion is one of the major drivers of deforestation and global biodiversity loss (Lambin *et al.*, 2001, 2003; Sandker *et al.*, 2017). Agricultural expansion and intensification often went hand in hand with agricultural intensification; some studies separated the two, whereas others did not (Delzeit *et al.*, 2017; Laurance *et al.*, 2014; Phalan *et al.*, 2013). Agricultural land expansion is a complicated issue and is underpinned by various drivers. New studies indicate that deforestation exhibited the strongest relation to rural population density, cost-distance and crop suitability, confirming that agriculture remains the major driver of deforestation (Sandker *et al.*, 2017). As a major driver, agricultural expansion has caused about 80% of deforestation in tropical regions (Rhett, 2012), and 50% in China (Houghton, 2002). The numerous agricultural activities that led to deforestation vary from region to region. Small-scale farming and fuel wood consumption are responsible for deforestation in Africa, whereas in Latin America, large-scale ranching, and especially cattle ranching, is the dominant driver of deforestation (Tscharntke, 2010). Here, cattle ranching often provides government with their main source of income (Geist & Lambin, 2002; Lambin *et al.*, 2001, 2003). More specifically, populations are increasing and need more food; incomes are increasing in many countries, driving the demand for meat, animal feed and other cash crops (Tscharntke, 2010). Since 1700, the world population has increased 11-fold, from 600 million to the current 7.7 billion (Roser *et al.*, 2013); the global expansion of croplands has led to the conversion of approximately 6 million km^2 of forests/woodlands and 4.7 million km^2 of savannas/grasslands/steppes since 1850 (Lambin *et al.*, 2001). Both the population growth and agricultural expansion trigger land scarcity (Lambin *et al.*, 2001). A recent study involving a cropland intensification scenario showed that cropland intensification has significantly increased production in places such as Africa (+78%), India (+68%) and the former Soviet Union (+63%) (Zabel *et al.*, 2019). The population is expected to reach 11 billion this century, when food production will be the primary challenge. Key priorities are improving technologies and policies to promote more ecologically efficient food production, while optimising the allocation of land to conservation and agriculture

(Laurance et al., 2014). Cropland expansion is another major driver of grassland degradation. Grasslands are one of the major types of land use in the world, covering about one - third of the Earth's terrestrial surface (Bengtsson *et al.*, 2019); they are crucial for livestock forage and wildlife habitat, and provide a livelihood for about 800 million people throughout the world (Wang *et al.*, 2018a). Besides providing food for animals, grassland plays an important role in the global carbon cycle, as well as in protecting plant species, animal habitats and soil, and cleaning water (Bengtsson *et al.*, 2019). Most grasslands are located in Asia and Africa, accounting for 33% and 28% respectively, with only a small share located in Europe and North America (7%) (Lambin *et al.*, 2003). Since the last century, however, grasslands have declined globally. Gant et al. estimated that about 50% of global grasslands have experienced degradation, and 5% extremely significant degradation, with the most severe degradation occurring in Asia (Gang *et al.*, 2014). Grassland degradation is generally defined as a decline in vegetation coverage and biomass production, which destroys the structure and function of soil, and causes erosion and desertification (Cao *et al.*, 2013; Wang *et al.*, 2018a). Overgrazing, climate change, cropland expansion and, conversely, a lack of management and abandonment are responsible for global grassland degradation (Bengtsson *et al.*, 2019; Hopkins & Holz, 2006; Queiroz *et al.*, 2014; Tiscornia *et al.*, 2019). Gang et al. (2014) showed that approximately 45.5% of grassland degradation was caused by climate change. The Millennium Ecosystem Assessment estimated that 10–20% of all grasslands have been degraded, mainly by overgrazing (FAO, 2015). Although many studies have estimated that overgrazing accounts for a large percentage of grassland degradation, leading to a loss of grazing capacity (Blair *et al.*, 2014; Cao *et al.*, 2013), the demand for livestock products continues to grow unabatedly. The FAO reports that livestock products will increase by 70% by 2050 (FAO, 2015), with severe overgrazing pressure occurring especially in Africa, the Middle East, Central Asia, the northern part of the Indian subcontinent, Mongolia, and northern China. Besides grazing, agricultural expansion is also responsible for grassland degradation in some regions. In the United States, about 77% of new cropland came from grassland between 2008 and 2012 (Lark *et al.*, 2015), while about 79% of pasture was converted from grassland in the Amazon region (Nkonya *et al.*, 2016). Other potential drivers, such as drought, policy management failures and cropland abandonment, are jointly responsible for grassland degradation. Taking action against grassland degradation could reduce poverty and promote carbon sequestration, whilst maintaining socio-economic, cultural and ecological benefits (Nkonya *et al.*, 2016). In a nutshell, all of the above-mentioned land use change processes have contributed significantly to urban land expansion.

Urbanisation is becoming the most important aspect of human social change in the world (Gu, 2019). More than half of the world's population now live in urban areas. By 2050, more than two-thirds of the world will live in urban areas (Ritchie & Roser, 2018). United Nations statistics showed that the world's urban population has increased significantly, growing from 751 million in 1950 to 4.2 billion in 2018 (2019). Asia has a slower urbanisation rate, but is home to 54% of the world's urban population, followed by Europe and Africa with 13% each. Today, the most urbanised regions include Northern America (with 82% of its population living in urban areas in 2018), Latin America and the Caribbean (81%), Europe (74%) and Oceania (68%). The level of urbanisation in Asia is now approximately 50%. In contrast, Africa remains mostly rural, with 43% of its population living in urban areas. Identifying drivers of urbanisation is crucial in respect to natural resource use, socio-demographics, health, and global environmental change (Haase *et al.*, 2018). The main drivers of land conversion vary in importance from region to region. For example, annual GDP growth was responsible for approximately half of observed urban land expansion in China, while population growth plays a more important role in India and Africa (Seto *et al.*, 2011). Gu et al. (2019) identified five major drivers of urbanisation: industrialisation, modernisation, globalisation, marketisation and administrative/institutional power. A natural increase in population and rural-urban migration are major drivers in developing countries (Tacoli & McGranahan, 2015). Rapid urbanisation has led to a set of environmental issues, such as the loss of biodiversity and ecosystem services, pollution and an increase in greenhouse gas (GHG) emissions (McDonald *et al.*, 2015; Yazdi & Dariani, 2019). These are exacerbated by housing, transportation, energy systems and other infrastructures, employment and basic services, especially in developing countries. It is clear that urbanisation will continue, that and promoting sustainable urbanisation is a key to successful development (Haase *et al.*, 2018; McDonald *et al.*, 2015).

1.2 The interaction between land use change and land degradation

Intensive land use change has led to serious land degradation across the world (Islam *et al.*, 2016; Lamchin *et al.*, 2016; Li *et al.*, 2009). Land degradation occurred in about 30% of the global land between 1982 and 2006 (Nkonya *et al.*, 2016). According to the IPCC report (Olsson & Barbosa, 2019), land degradation was defined as "*a negative trend in land condition, caused by direct or indirect human-induced processes including anthropogenic climate change, expressed as long-term reduction or loss of at least one of the following: biological productivity, ecological integrity or value to humans.*" This definition was applied to different aspects, where forest degradation signifies degradation that has occurred in forest areas and soil degradation refers to a set of processes that affect soil quality. By definition, land degradation is generally described as a reduction in ecosystem services. Dramatic global land use change led to land degradation due to negative effects on soil quality, a loss of biodiversity, and a decreasing of land production. Various negative effects of land use change, such as forest loss, have reduced biodiversity; grassland degradation has led to soil erosion; and cropland intensification has led to an increase in soil organic carbon. Furthermore, land degradation is a driver of climate change due to GHG emissions and reduced rates of carbon uptake (Olsson & Barbosa, 2019). Based on economic assessments, the cost of land degradation due to LUCC accounts for 78% of the total global cost of land degradation of about USD 300 billion, suggesting that the priority task is to address the land degradation caused by land use change (Nkonya *et al.*, 2016). Conversion of forest to grazing land is the major driver of deforestation in the Amazon region, whereas the conversion of grassland to bare land and shrubland is the major driver of grassland degradation in Central Asia (Nkonya *et al.*, 2016). Identifying the processes and patterns of land degradation and its drivers is important for combating land degradation. However, many previous studies have analysed land degradation based on only one type of land use change process, such as forest land degradation (Barlow *et al.*, 2016; Dlamini, 2016; Rudel *et al.*, 2009), or used a proxy to illustrate land degradation (Bai *et al.*, 2008; Eckert *et al.*, 2015). This thesis goes a step further by illustrating land degradation based on a detailed analysis of processes and patterns of land use change. Land degradation can be avoided, reduced or reversed by implementing sustainable land management and restoration or rehabilitation practices that simultaneously provide many co-benefits, including adaptation to and mitigation of climate change. From this perspective, identifying the major drivers of land degradation is crucial to any national or international efforts made to reduce and, ideally, prevent land degradation and promote land restoration and improvement.

2 Motivation and research gap

2.1 The socio-economic context of land use change on the Mongolian Plateau

The Mongolian Plateau contains the largest grassland in the world (Miao *et al.*, 2017). Mongolia is famous for being the cradle of nomadic civilisation and for its vast grasslands, the Gobi desert, and the stories of Genghis Khan and his Mongol Empire (Wu *et al.*, 2015b). The Mongolian Plateau is part of the Central Asian plateau, hinterland of temperate Asia. It is sparsely populated, and has rich mineral and grassland resources. The region is controlled by a continental and semi-arid to arid climate, characterised by low precipitation, high evapotranspiration, large temperature amplitudes, long and harsh winters and recurrent droughts (Na *et al.*, 2019). The region compromises two parts: the Inner Mongolia (IM) Autonomous Region of China, and the Republic of Mongolia (RM) (Wang et al., 2013, see Figure I-1). The whole region covers an area of 2.75 million km^2, with 1.18 million km^2 in Inner Mongolia and 1.57 million km^2 in Mongolia. Inner Mongolia has a population of about 28 million, and the Republic of Mongolia is home to 3 million (Fang *et al.*, 2015). The Mongolian Plateau is an essential part of the world's drylands, which account for 40% of the global land and 38% of the global population. Land use change on the Mongolian Plateau is not unique, and has undergone profound processes of land use change and land degradation (Fang *et al.*, 2015; Wu *et al.*, 2015b). Thus, this thesis, focusing on land use change and degradation on the Mongolian Plateau, has relevant implications for arid and semi-arid landscapes around the world.

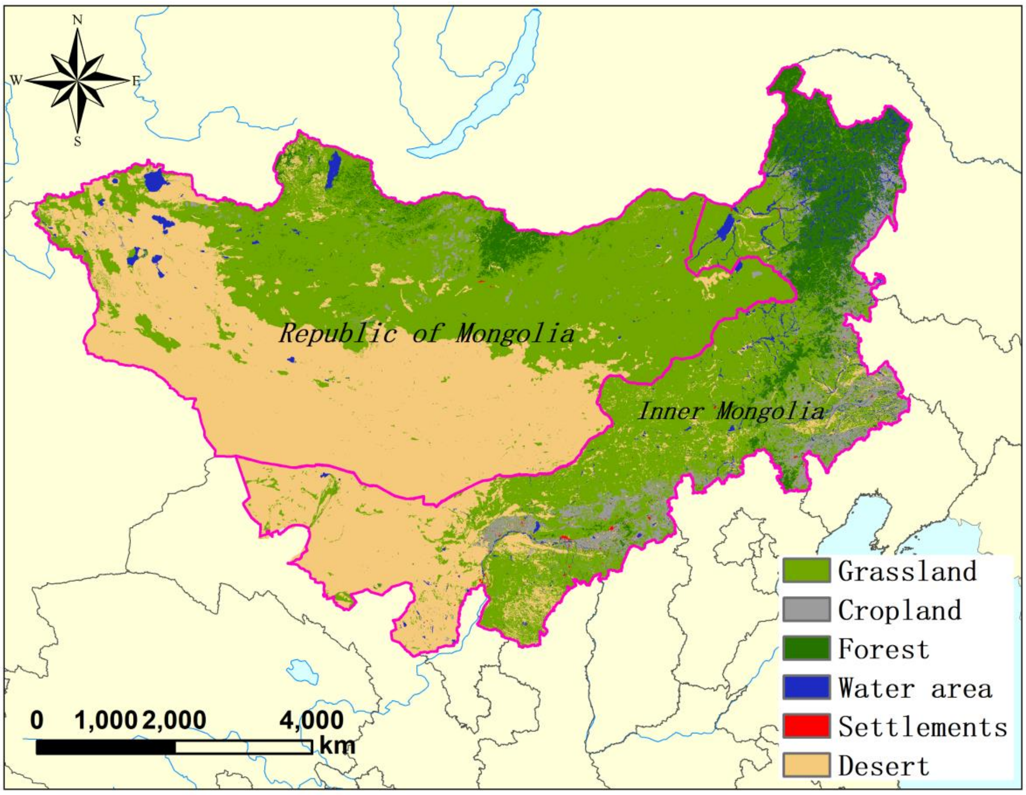

Figure I-1: Land use types on the Mongolian Plateau
(Data sources: State Key Lab Resources & Environment Information System, Institute of Geographic Sciences and Natural Resources Research，CAS.)

The plateau was converted from an ancient ocean to a forest region over the course of millions of years, and then changed to a dryland area. The vast grassland was formed about 2.4 million years ago (Fang et al., 2015; Wu et al., 2015b). Due to the impacts of glacial and interglacial events during the early Quaternary Period, the climate became even drier and cooler, with deserts and sandy land gradually emerging (Wu et al., 2015b). The dominant type of land use on the plateau is grasslands and deserts, formed 2 million years ago, accounting for 44% and 34% of the total land area respectively, also including forests (14%) (Figure I-1). Inner Mongolia and the Republic of Mongolia separated in 1940; both subregions encompass the same nomadic culture, lifestyle and language, but use different words. After separation, both Inner Mongolia and the Republic of Mongolia experienced quite different land use policies in recent decades, leading to contrasting socio-economic and environmental changes in the two parts of the same plateau. Land use change in Inner Mongolia is a more intensive process of land use change than in the Republic of Mongolia (Wu *et al.*, 2015b).

Inner Mongolia is located in the north of China, accounting for 12% (1.18 million km^2) of China's territory. Grassland is the major type of land use, covering 0.75 million km^2 (statistical value, the figure in the land use database is about 0.47 million km^2). People appeared in this region around 700 thousand years ago, and Inner Mongolia became the cradle of nomadic culture in China (Wu *et al.*, 2015b). Ever since grassland appeared in this region, the landscape has experienced significant change, mainly because of the cold and dry weather (Wu *et al.*, 2015b). Inner Mongolia has faced multiple challenges since 1949 (when the "People's Republic of China (PRC)" was founded) due to land use and ecological conditions, such as land tenure, land use policies, land use and vegetation dynamics, and the grazing industry.

Xilingol was chosen as the case study due to its landscape features, with a high proportion of natural grassland, and the Mongolian population; about 86% of the total area is covered by grassland (Figure I-2). This region experienced severe degradation between the 1950s and 1960s, which accelerated in the 1980s up to the 1990s; 70-80% of the total grassland area has been degraded (Huang *et al.*, 2009b: 3). Xilingol lies north of Beijing, and plays a significant environmental role. Xilingol also exhibited an obvious trend towards restoration after the year 2000 (Li *et al.*, 2012b). Furthermore, being a typical arid and semi-arid region, Xilingol has experienced almost all ecological policies implemented by the central government in China. Since Central Asia has similar problems (Kemp *et al.*, 2018), finding a better way to manage grassland and improve herders livelihoods is crucial for local sustainability management, not only for the Mongolian Plateau, but also for the whole of Central Asia. It would even benefit dryland regions. Against this background, Xilingol is a typical region for providing a comprehensive understanding of land use change and land degradation on the Mongolian Plateau. It is also a good case for understanding the causal relationship between drivers and degradation.

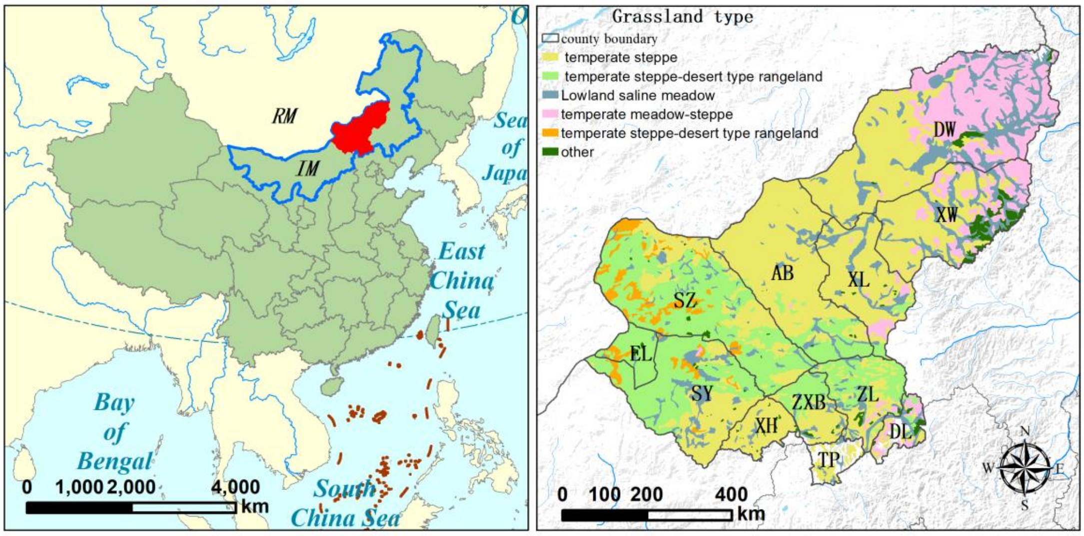

Figure I-2: Location of the study area
(Data sources: http://www.resdc.cn/)

2.2 Ecological issues on the Mongolian Plateau

The Mongolian Plateau has recently experienced serious environmental issues and drastic land use change (Ge *et al.*, 2018; John *et al.*, 2009). In a bid to identify current ecological problems, we have summarised the current status of ecological progress reported by various research groups and individuals throughout the world.

In his PhD thesis at Humboldt-Universität zu Berlin, Yin He used coarse-resolution image data to identify processes of land use change at frequent intervals (yearly) since the implementation of ecological projects in Inner Mongolia. The results showed land restoration programmes have improved the forest increase rate and cropland retirement rate (Yin, 2014). Land use policy is seen as the major cause of significant land use change in Inner Mongolia. Professor Wenjun Li and her group from Beijing University, China, have clarified the historic land use policy frame in Inner Mongolia. She reported that before “land property reformation”, the State was the land owner, and livestock belonged to herders, which led to the “tragedy of common”, with grasslands starting to degrade (Akram *et al.*, 2009; Fan *et al.*, 2014). In contrast to the “tragedy of common”, Min Liu, a PhD student from Wageningen University, coined the “tragedy of privatisation”. In her PhD thesis, she reported that the privatisation of land and livestock has limited the mobility of livestock. Mobility is the most salient characteristic of nomadic culture, easily distinct from agrarian culture. Mobility refers to herders and livestock moving seasonally and yearly, to avoid overgrazing and harsh weather (Kemp *et al.*, 2018). Mobility is an important way to allow local herders to retain their nomadic culture and to adapt to harsh weather; it has enabled the overuse of grasslands to be avoided on the Mongolian Plateau for thousands of years (Kemp *et al.*, 2018; Wu *et al.*, 2015b). Based on this, Wenjun Li et al. suggested that the development of a semi-nomadic grazing system increased mobility (Bijoor *et al.*, 2006; Fan *et al.*, 2014; Li *et al.*, 2007).

In a bid to combat grassland degradation, a set of ecological policies was implemented after 2000. However, all policies have led to new ecological change in the region, affecting not only socio-economic and ecological conditions, but also having a significant effect on ecosystem services and livelihoods. Bingzhen Du has evaluated the trade-offs between human activities, the use of ecosystem services and human well-being in her PhD thesis. The results showed that these policies affect ecological measures, which have an impact on households’ livelihoods, such as household food consumption, water consumption, fuel consumption, farmers’ job options, animal feed options and herder’s income. Besides focusing on policies, some scholars have also focused on the system of herders keeping livestock on grassland to explore the causes and measures that curb ecological degradation. Britta Mareike Bösing of the Christian-Albrechts-Universität zu Kiel evaluated the effects of different grazing strategies in her PhD thesis. The results showed the importance of reducing livestock density to mitigate winter soil erosion by wind, and of supplementing feed over a few months to alleviate grazing pressure and increase long-term grassland productivity (Bösing, Britta Mareike, 2013).

Furthermore, Xiangzheng Deng, a researcher from the Institute of Geographic Sciences and Natural Resources Research, CAS, and his research group explored the plausible future combined with multiple scenarios analysis, analysing changes in ecosystem services and its drivers in Inner Mongolia. The study suggests that the local government should plan the rational exploitation of land resources, adjust the economic structure, and control population growth and economic development; in addition, climate factors also have negative effects on ecosystem services in this region (Wang *et al.*, 2017; Zhan J Y *et al.*, 2007). Allington et al. (Allington *et al.*, 2017, 2018), in contrast, used a non-spatial model to explore the interaction between grassland productivity, livestock and human populations, nature and processes of land use change on the Mongolian Plateau.

Jiquan Chen, a Professor at Michigan State University, attempted to couple the human system and natural systems with his lab in a bid to understand the complex relationships and feedback between the human system and natural systems. He contributed the coupled natural and human system (CNH) conceptual framework demonstrating the drivers, mechanisms and consequences of socio-economic and physical changes on the functional changes of the human system and natural systems on the Mongolian Plateau (http://lees.geo.msu.edu /research/cnh_mongolia.html). Jikun Huang, a researcher from the Center for Chinese Agricultural Policy, CAS, analysed the effects of ecological construction programmes, such as the effects on livestock production and grassland conversion (Hu *et al.*, 2019; Liu *et al.*, 2018). Other researchers such as Yongfei Bai analysed the grassland community structure and biodiversity, including grazing and climate drivers, the consequences of soil quality and adaptive management of grassland ecosystems.

To sum up, issues related to land degradation have attracted great attention across the world. Other researchers who focused on specific ecological objectives, such as grassland degradation (Williams, 1996; Zhang *et al.*, 2016b), lake area shrinkage (Tao *et al.*, 2015a; Zhou *et al.*, 2019), rapid urbanisation (Bulag, 2002; Fan *et al.*, 2016; Huang & Jiang, 2017; Park *et al.*, 2017), deforestation (Juřička *et al.*, 2018, 2019), desertification (Wei *et al.*, 2018) and agriculture displacement (Batunacun *et al.*, 2018) have also been widely reported. In addition, the consequences of these ecological issues have also been extensively discussed. Grassland degradation has led to a reduction in organic soil (Fu *et al.*, 2011), reduction in biodiversity (Wu *et al.*, 2015a), carbon sink loss and water loss, an increase in dust storms and soil degradation (Cao *et al.*, 2013; Liu *et al.*, 2006), more frequent extreme weather (Mang-Mang Gou *et al.*, 2010), a decrease in output of livestock products (Dietz *et al.*, 2005), and even changes in people's livelihoods (Waldron *et al.*, 2010; Xu *et al.*, 2012; Zhang *et al.*, 2017). Sudden land use changes have also led to a serious deterioration of ecosystem services on the Mongolian Plateau. Xu et al. (2018) and Du et al. (2019) showed that desertification has led to a serious loss of ecosystem service value (ESV), while grassland biodiversity decreased between 1968 and 2008 (McGovern *et al.*, 2011) and above-ground biomass increased after 2000 (Li *et al.*, 2019).

Above all, the major ecological issues, as well as their major drivers and consequences, on the Mongolian Plateau have been identified by extensive analysis. The system of herders keeping livestock on grassland, the change in ecosystem services, herders' behaviour, decision-making processes and grassland degradation processes have been analysed in this region. However, some research gaps still remain in this region, and an integrated and systematic understanding of land use change and its driver dynamics is still required. Most of these studies are based on individual aspects of ecological effects in this region. More researchers should focus on the underlying drivers of land use change and land degradation, not only the symptoms of degradation. To increase the likelihood of the success of sustainable transformation, it is important to examine past evolving trajectories, to identify key variables and their interactions, and to understand how they result in fundamental structural change. This thesis gives greater attention to historical, systematic and integrated aspects in a bid to better understand ecological issues such as dramatic land use change and grassland degradation. It also provides more insight into land use change and its drivers by applying different methodologies.

2.3 Determinants of LUCC and its approaches in Inner Mongolia

One of the key activities of land use and land cover change studies is to simulate syntheses of land use change processes, and in particular, advance our understanding of the causes of land use change (Geist *et al.*, 2006). Land use patterns result from decision-making and land actors, which are influenced by many ecological, societal, economic and climatic factors. These drivers can be divided into two categories: proximate drivers and underlying drivers. Proximate drivers generally operate at a local level and are direct drivers. Underlying drivers generally underpin more proximate circumstances, operate more diffusely, and are the root or indirect cause of change (Geist *et al.*, 2006). Changes in underlying drivers generally lead to changes in proximate drivers, triggering land use and land cover change (Geist *et al.*, 2006). Underlying drivers are difficult to identify due to their gradual temporal change and low spatial variability (Kleemann *et al.*, 2017; Shao *et al.*, 2006). Understanding drivers of land use change is crucial for revealing the motivation behind regions' LUCC; it is also important for decision-making and for place-specific sustainable land management, enabling researchers to simulate and predict processes of land use change (Shao *et al.*, 2006). Above all, drivers of LUCC and complex interactions among socio-ecological systems differ at various spatial scales, making it difficult to identify and understand them (Kleemann *et al.*, 2017). Moreover, it is difficult to ranked drivers of LUCC and their previous ranks (Shao *et al.*, 2006). Consequently, major drivers and complex interactions must be identified to enable further research. Determining the root cause of land use change could mean that policies no longer focus on symptoms only, but also on the fundamental processes requiring remedial action (Campbell *et al.*, 2005).

The causes of grassland degradation on the Mongolian Plateau have been widely discussed by many researchers. The causes identified include land tenure reform (Akram *et al.*, 2009; Bijoor *et al.*, 2006), overgrazing (Han *et al.*, 2008), climate change (Ibrahim *et al.*, 2015; Sun *et al.*, 2017), mining development (Qian *et al.*, 2014, Tao *et al.*, 2015; Zeng *et al.*, 2018), agricultural expansion (Fang *et al.*, 2015; Wu *et al.*, 2015b), excessive reclamation (Batunacun *et al.*, 2018) and frequent drought (Hessl *et al.*, 2018; Liu *et al.*, 2019b). However, the use of different methods has led to the identification of quite different contributions made by these drivers in Inner Mongolia (Li *et al.*, 2012a, 2012a; Sun *et al.*, 2017). Statistics-based methods, logistic regression and principle component analysis are often used in such studies. Statistical approaches identify the influence of independent variables, and also fit the spatial process of land use change well; model results are easy to understand and interpret (Dimobe et al., 2015; Ellis et al., 2010; Kim et al., 2014; Liu et al., 2013a, 2014b; Rutherford et al., 2007; Wu et al., 2015b). Likewise, the prior assumption is that the relationship between land use change and its drivers is linear (Adhikari *et al.*, 2017; Bao *et al.*, 2017; Kim *et al.*, 2014). However, since the relation between drivers and land use is complicated, as are their interactions, such assumptions seem oversimplified. This may lead to an inaccurate description of land use change patterns or the characterisation of the human land system by non-linearities (Chen *et al.*, 2015; Geist & Lambin, 2002; Verburg *et al.*, 2004). In addition, other mono-linear methods have been used to explore a number of specific effects of drivers. For example, Allington et al. (2017, 2018) used a non-linear model, a system dynamic model, to explore four different scenarios for Xilingol, identifying the plausible livestock pressure based on stakeholder participation. Liu et al. (2018) used econometric methods to evaluate policy effects on grazing and grassland in Inner Mongolia. However, these methods suffer from a loss of spatial information, and are unable to provide sufficient information to support decision-making.

Against this background, different methods at different spatial scales should be developed to understand the underlying drivers of land use change, as well as to break through such limitations. In this thesis, a holistic approach was taken, using Partial ordering theory and Hasse diagram techniques across disciplines with a focus on comparing and ranking existing drivers of land degradation at the county level. Hasse diagram techniques were used to visualise the partial order relation between these drivers, the major drivers were extracted during the ranking process for each county. The county was considered the basic administrative unit in China; identifying drivers at the county level enables ecological and socio- economic conditions to be reflected on. Comparing and ranking drivers at the county level is crucial for policy implementation and adaptation. Once the major drivers have been identified at the county level, the impact of those drivers on degradation needs to be researched.

With the development of computer science, data-driven methods provide great potential to explore the complex relationship of the human-nature system. Data-driven methods seek to explore patterns in large data sets (Mileva Samardzic-Petrovic *et al.*, 2018). They cover two important fields: machine learning (ML) and data mining (DM). Data-driven methods were introduced to simulate and predict land use change. ML and DM are closely related, and their concepts overlap. ML aims at mimicking a self-organised learning process, which enables the machine to continuously improve a given task. ML generates knowledge from existing data and experience. DM is a method developed to analyse large and complex datasets, motivated by practical needs (Clauset *et al.*, 2017; Ho *et al.*, 2016; Subramaniyan *et al.*, 2018).

Machine learning models have been identified as a useful model for simulating the complex relationship between the natural system and the human system (Ahmadlou *et al.*, 2016; Dlamini, 2016; Duraisamy, 2018; Filippi *et al.*, 2014). These models are freely available, it is easy to organise the data structure, and they well-suited to understanding complex relations between the human system and the natural system (Ahmadlou *et al.*, 2019; Samardžić-Petrović *et al.*, 2017). Boosted tree-based algorithms in particular work with a high degree of accuracy, effectively handling the non-linear relationship and interactions, and improving overfitting and missing data (Chen & Guestrin, 2016). One disadvantage of ML methods is that the complex relationship is managed in a black box, which is difficult to understand. In this thesis, the author opened the black box and attempted to visualise the complex relationship between drivers and grassland degradation. The complex relationship was visualised using an ML model and SHAP values, a new method developed in recent years. SHAP values have a great potential to open the black box combined with another black box model.

2.4 Contribution of this thesis

There are two fundamental steps in any land change study: detecting changes in the landscape, and ascribing that change to some set of causal factors (Kleemann *et al.*, 2017). The contribution of this thesis focuses on these two topics, summarising them into two aspects: provision of a comprehensive understanding of land use change and its drivers, and an improvement in the state of methodology in identifying drivers of land use change and simulating degradation dynamics on the Mongolian Plateau. First, this thesis provides a regional land use change inventory in Xilingol over space and time. Taking Xilingol as a case study, this thesis provides the land use profile for the Mongolian Plateau. In addition, land degradation is detected based on the analysis of land use change. This thesis analyses historical land use conversion patterns and processes between 1975 and 2015. The major spatial patterns of land use change in Xilingol are mapped and quantified in this thesis, detecting the location and intensity of change. Based on detailed land use conversion processes, land degradation and restoration were identified in the study region. In the process, two steps were necessary to ascribe drivers of land use change. The first step was to identify the major driver of land degradation for each county for two different phases. The second step relied on extracting comparative information to explore the driver dynamics related to land degradation dynamics in two periods. ML methods were used to reveal the non-linear relationship between drivers and degradation. This contributed to our understanding of the complex relationship between the human system and nature the system without having to make any assumptions.

Above all, clustering approaches such as partial order theory (POR) and Hasse diagram techniques (HDT) are useful tools for exploring the major drivers of degradation. In addition, POR and HDT were first used to identify the drivers of land use change. Once the major drivers had been determined, XGBoost and SHAP values were used to capture and visualise the complex relationships between drivers and degradation. In this thesis, we provide a comprehensive understanding of land use change and land degradation. Subsequently, these new methodologies contribute to new insights into land use change and its causes. It is hoped that the research and methodologies described in this thesis will stimulate further interdisciplinary research on land use change and land improvement, especially at the local level.

In conclusion, the main contribution of this thesis is to provide a more systematic and integrated study of land use change and its drivers on the Mongolian Plateau. This would be useful for sustainability management on the Mongolian Plateau and for improving ecological degradation so as to explore the potential to alleviate the impact of global climate change, helping communities to adapt to climate change or even retain their traditional nomadic culture. This thesis used partial order theory to compare and rank drivers of land degradation at the county level; the black box was then cracked open to visualise the complex relationship between drivers and grassland degradation at the pixel level. The study enriches the methodology of identifying drivers of land use change, and improves the state of technology and methodology.

3 Conceptual framework

3.1 Research questions and objectives

The overall aim of this dissertation is to gain a better understanding of the process of land use change and to capture the complex relationship between the dominant land use change process (degradation) and its drivers at different spatial scales. Insensitive land use change resulting in vast land degradation has attracted great attention across the world (Barbier, 1997; Geist & Lambin, 2002; Gisladottir & Stocking, 2005; Huang & Kong, 2016). Various institutional and political measures have been implemented around the world to combat land degradation (Conacher & Conacher, 2001; Gollnow & Lakes, 2014; Liu *et al.*, 2017). China, an ambitious engineering country, has launched a set of different policies to combat environmental deterioration (Qiu *et al.*, 2011; Wang *et al.*, 2012; Zhang *et al.*, 2016a), and important progress has been made under these policies (Chen *et al.*, 2019).

While great efforts and massive investment have aimed at combating land degradation and improving the livelihoods of local herders, a comprehensive understanding of land degradation processes and causal relationships in the circle of land use change, policy transformation and driver dynamics is as yet missing. Moreover, a non-linear method is needed to simulate grassland degradation in this region. Consequently, three overarching research questions were addressed as following in this thesis.

<u>Research Question 1:</u> *How did land use/land cover and land degradation change in Xilingol between 1975 and 2015?*

Two objectives were included to clarify this question:

Objective 1: *Analyse the spatial and temporal pattern of LUCC in Xilingol between 1975 and 2015;*

Objective 2: *Evaluate land degradation, especially grassland degradation, on the basis of this analysis*

Xilingol has experienced almost all ecological policies that have been implemented in China since 2000. However, the aim is to determine whether processes of land use change process were different before and after the launch of ecological engineering programmes. Against this background, micro - spatial and long - term scale remote sensing data were used to explore this question. The spatial and temporal patterns and processes of land use change in study region since 1975 were analysed, and the trends of land degradation and restoration processes were identified based on different land use change processes. A comprehensive understanding of land use change processes and land degradation patterns was provided in this study. The results showed that the year 2000 was the turning point for land use change.

Research Question 2: *How can we identify drivers of land degradation and grassland degradation at the county level?*

Three objectives related to this research question were as follows:

Objective 1: *Analyse temporal and spatial LD driver dynamics in Xilingol;*

Objective 2: *Compare and rank LD drivers at the county level;*

Objective 3: *Summarise the ecological policies and measures that were initiated in Xilingol between 1980 and 2020, and discuss possible policy measures for the future.*

How can we explain why 2000 was a turning point for different land use change processes? What was the dominant determinant for land degradation at the county level? The county/banner is the third level in China's administrative hierarchy, below the level of provinces and prefectures. Since counties have their own administrative government, identifying major drivers at the county level is a crucial prerequisite for county governments to create or improve their regional land use plans. The partial order theory and Hasse diagram technologies were used in combination to address these questions. The results show that, due to the ecological measures implemented to control human disturbances, human disturbance was no longer the responsible driver of land degradation in most counties after 2000. In addition, this question revealed the causal relationships between land use change and drivers.

Research Question 3: *How can we gain a better understanding of the relationship between drivers* *and grassland degradation?*

This question was addressed using two detailed objectives:

> <u>*Objective 1:*</u> *Can machine learning models achieve a better predictive quality than linear methods?*
>
> <u>*Objective 2:*</u> *How can we open the non-linear relationships of the black box model?*

How does each driver influence the grassland dynamics, and can non-linear method simulate grassland dynamics better? The land use system is a complex and interacted system. However, most land use models have simplified these interactions and causal relationships, with some assuming that the relationship between drivers and land use change is linear, and yet the real world is more complex and interactive than that. In addition, the black box is not an easy method to understand. However, it is important that ecologists and decision-makers understand the complexity of the black box. A robust model based on non-linearity was created to simulate grassland dynamics, and a recently developed tool was used to crack the black box.

3.2 Structure of this thesis

This cumulative thesis comprises five section. Chapter I provides an introduction to the scientific background of the study, and the comprehensive introduction to the study and structure of this thesis. Chapters II-IV are the core sections of the thesis. Chapter II determines how land use has changed and was degraded in Xilingol over the past forty years, using remote sensing images, a geographical information system (GIS) and statistical methods. Chapter III identifies the dominant drivers of land degradation at the county level, using a clustering approach, partial order theory (POT) and Hasse diagram techniques (HDT). Against this background, a black box method (XGBoost: eXtreme Gradient Boosting) and a tool to avoid black box (SHAP values) were used to visualise the relationship between grassland degradation and its drivers, as well as to predict the spatial grassland degradation dynamics. The logical relationship between these three sections is visualized in Figure I-3. Chapter V provides a synthesis and conclusion, summarizing the key results and providing an outlook.

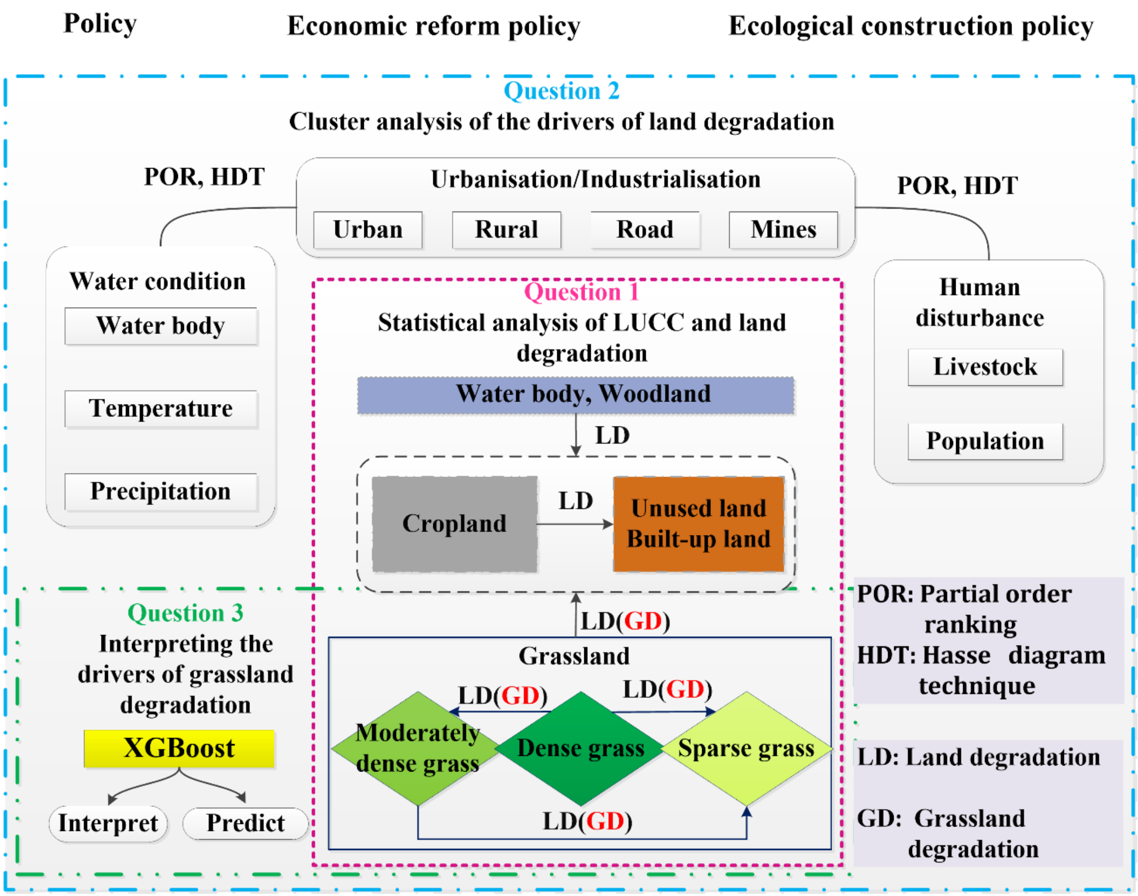

Figure I-3: Schematic overview of the conceptual framework of this study

The core chapters (Chapters II–IV) are the main chapters of this dissertation, which have been published in international, peer-reviewed journals.

Chapter **II** ***Batunacun***, *Claas Nendel, Tobia Lakes* (2018). Land-use change and land degradation on the Mongolian Plateau from 1975 to 2015 — a case study from Xilingol, China. *Land degradation and development, 29, 1595–1606*

Chapter **III** ***Batunacun***, *Ralf Wieland, Tobia Lakes, Claas Nendel (2019).* Identifying drivers of land degradation in Xilingol, China, between 1975 and 2015. *Land Use Policy, 83, 543–559*

Chapter **IV** ***Batunacun***, Wieland R, Lakes T, Nendel C. 2020. Using SHAP to interpret XGBoost predictions of grassland degradation in Xilingol, China. Geoscientific Model Development Discussions 1–28.

Chapter II:

Land-use change and land degradation on the Mongolian Plateau from 1975 to 2015 — a case study from Xilingol, China

Land degradation and development, 2018, Volume: 29, Pages: 1595-1606

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Abstract

Land degradation is a severe environmental problem on a regional and global scale that is often aggravated by intensive land-use and climate change. The arid to semi-arid Xilingol in Inner Mongolia, China, is an example of an area that has witnessed continuous land degradation for decades, in spite of numerous attempts to reverse this trend. In this study, land-use and land-cover change (LUCC) between 1975 and 2015 was investigated for Xilingol based on multi-temporal remote sensing images. The aim of the study was to derive detailed information on LUCC over space and time as a basis for assessing ecological and social consequences of land degradation in a bid to develop better strategies for combating land degradation. Two main LUCC processes and two distinct phases were identified: during Phase 1 (1975–2000), the LUCC pattern was dominated by land degradation, affecting 11.4% (22,937 km^2) of the total area. During Phase 2 (2000–2015), land restoration increased (12.0%, or 24,161 km^2) while degradation continued, resulting in a further 9.5% (19,124 km^2) of degraded land. The transition pattern changed accordingly. Our findings show that, in spite of notable restoration successes in the past, grassland degradation continues to be the main ecological and environmental problem in Xilingol, requiring the continued attention of decision-makers. Strategic land-use management has already had a significant influence on LUCC in this area, leading to the expectation that science-based land-use strategies can be developed to further reduce land degradation in Xilingol.

1 Introduction

In many parts of the world, land-use and land-cover change (LUCC) has had various effects on natural systems and societies. Examples have been reported where LUCC has increased pressure on resource production, and influenced climate change (Lambin *et al.*, 2001), biodiversity (Falcucci *et al.*, 2007) and soil erosion (Yang *et al.*, 2003), as well as threatening food security (Liu *et al.*, 2005) and even causing land degradation (Lambin *et al.*, 2003). Land cover refers to the biophysical attributes of the earth's surface, and land use refers to human purpose or intent applied to these attributes. Climate-driven land cover modifications interact with land-use changes (Lambin *et al.*, 2001). Understanding the primary causes and examining the process and trends of land-use change is a crucial prerequisite for sustainable and appropriate land-use planning, the use of regional resources and environment management (Zhao *et al.*, 2012). Land degradation is a complex process involving two interlocking systems: the natural ecosystem and the socio-economic system (Bajocco *et al.*, 2012; Zhang *et al.*, 2007). Great attention has been given to regional land-use changes in the north of China, especially in the arid and semi-arid areas of Inner Mongolia, where economic development, population growth and climate change have induced significant land-use changes in the past (Chen *et al.*, 2003; Deng *et al.*, 2011; Hao *et al.*, 2014; John *et al.*, 2009). Land degradation in the sense of this study is defined as any loss of soil quality, productivity, species richness, livelihood, or in the provision of other ecosystem goods and services, ranging from slight decline to complete destruction or transition into different land use (Dai *et al.*, 2014; Lambin *et al.*, 2003; Zhang *et al.*, 2007). Severe land degradation has occurred in northern China and on the Mongolian Plateau (Zhang *et al.*, 2005, 2005). Grassland degradation caused by irrational land-use (urbanisation, cultivation) and overgrazing was the main land degradation process in Inner Mongolia in recent decades (Hao *et al.*, 2014; Li *et al.*, 2012a, 2012b). In the context of this study, grassland degradation refers to a process of decreasing grassland production and deteriorating ecosystem conditions (Li *et al.*, 2012b; Liu *et al.*, 2008), commonly resulting in a significant reduction in plant biomass and coverage (Hao *et al.*, 2014) and the complete destruction and subsequent use of land for other purposes (Dai *et al.*, 2014). In the framework of Andrade*, et al.* (Andrade *et al.*, 2015), the latter aspect is subdivided into land-use changes from which original grassland can be restored (e.g. cropland) or not (e.g. built-up land). However, restoration potential is not always readily apparent for some land-use changes. Examples include the temporary human land-consuming activity of mining, and desertification – the climax of a reduction in grass biomass and cover. Restoration is commonly defined as “returning to an original state and to a state that is perfect and healthy state” (Bradshaw, 1996). However, as the intentional character of a land-use change cannot be confirmed from space, we define restoration as any expansion of grassland, water bodies and woodland due to transformation from unused land and cropland in the context of this work. Beside this, any improvement of grassland coverage is referred to as “revegetation” further below. Our study involved evaluating grassland degradation based on grassland coverage—using three cover classes to distinguish different grades of degradation severity—and area change (former grassland being transformed into other land-use types).

Previous studies based on observational data (Hao *et al.*, 2014; Li *et al.*, 2012b) and remote sensing products (He *et al.*, 2015) involved evaluating land degradation or restoration in a specific area using a single indicator only. There is a lack of studies that identify and characterise land degradation patterns and processes in a bid to gain greater understanding of the role played by the land degradation process in land rehabilitation (Andrade *et al.*, 2015). This is particularly the case in arid and semi-arid areas, such as in Xilingol, which has a highly sensitive and vulnerable ecosystem.

Against this background, the objective of our study was to identify current trends of land degradation and restoration in Xilingol on the micro-spatial and long-term scale using remotely sensed (RS) data backed by ground studies. Earlier studies have shown that RS images can provide credible data sources for grassland degradation/restoration (Li *et al.*, 2009; Liu *et al.*, 2008; Tong *et al.*, 2004). The integration of multi-temporal and multi-spatial remote sensing data to produce land-use type trajectories provides new insight into the history of LUCC in many cases. The specific objectives of this study were to: (1) analyse the spatial and temporal pattern of LUCC in Xilingol between 1975 and 2015 and (2) evaluate land degradation, especially grassland degradation, on the basis of this analysis.

2 Materials and methods

2.1 Study area

Xilingol, located in the centre of Inner Mongolia, is renowned for its vast grasslands and nomadic culture. The study area covers a total of 206,000 km^2, spanning a latitude of 41.4°N to 46.6°N and a longitude of 111.1°S to 119.7°S (Figure II-1). The region was chosen as a case study because of its particularly fragile ecosystem, which has developed under arid and semi-arid continental climate conditions. Xilingol grasslands have been affected by degradation in recent decades, resulting in desertification in some parts. Grassland degradation in Xilingol was first noticed in the 1950s, and described in terms of encroachment by shrubs, decrease of density, height and biomass of forage plants, absence of previously dominant species, increase of the sand fraction in soil textures and first signs of salinisation (Huang *et al.*, 2009b). By the end of the 1980s, degraded rangelands accounted for 48.6% of the total land in the study area, increasing to 70–80% by the end of the 1990s. Land degradation in Xilingol has led to many secondary ecological and environmental problems: the frequency and severity of sands storms have increased (Liu *et al.*, 2013) and the ecological carrying capacity has decreased (Yang *et al.*, 2011).

The topography of the study area consists of gently rolling hills, tablelands and sand dunes, with elevations between around 1000 and 1300 m (Bai *et al.*, 2007). Xilingol has a mean annual temperature of 2.2°C (varying between 2.3 and 5.6°C) and a mean annual precipitation of 278 mm (varying between 135 and 433 mm). Soils in this area follow an obvious pattern from the southeast to the northwest, ranging from chernozem to light and dark chestnut soils (Hao *et al.*, 2014). Vegetation types in the study area include various formations of desert steppes, typical steppes and meadow steppes (Hao *et al.*, 2014).

The ecological system pattern in Xilingol is characterised by two main gradients: the first is a natural ecosystem gradient with forest in the east, then meadow steppe–typical steppe–desert steppe–steppe desert descending towards the west. The other obvious gradient follows cropland over interlaced agro-pastoral to animal husbandry areas from south to north. The first gradient is the result of the natural variation of soil and climate dominance; the second pattern represents the boundary and transition of human intervention (Hu *et al.*, 2013).

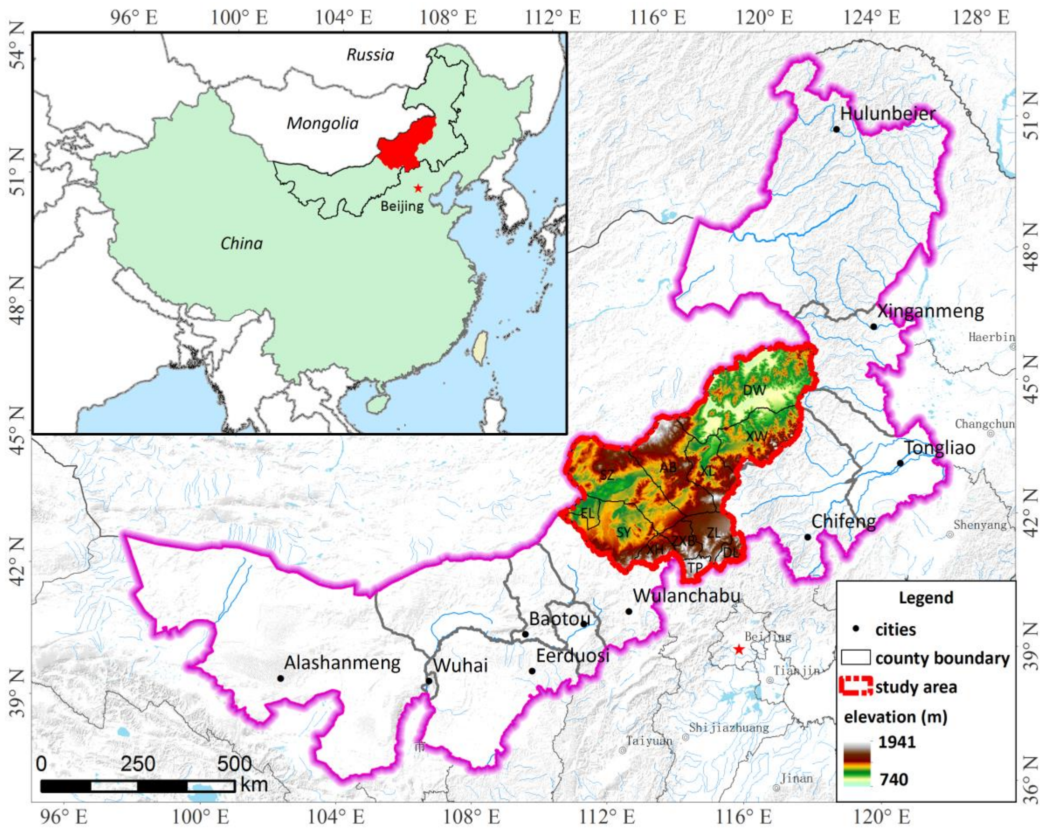

Figure II-1: Xilingol within Inner Mongolia and China.
Notes:DW Dongwuzhumuqin Banner, XW Xiwuzhumuqin Banner, XL Xilinhot, AB Abaga Banner, SZ Sunitezuo Banner, SY Suniteyou Banner, EL Erlianhot, XH Xianghuang Banner, ZXB Zhengxiangbai Banner, ZL Zhenglan Banner, DL Duolun, TP Taipusi Banner.

2.2 Materials

2.2.1 Remote sensing images and auxiliary data

A total of 203 scenes from Landsat MSS/TM/ETM+/OLI (https://www.usgs.gov/) for the years 1975, 1990, 2000, 2005 and 2015 and HJ-1 scenes (http://www.secmep.cn/secPortal/portal/indexLogin) for the year 2009 were used as the key information sources for this study. Most of the image data for this study were acquired during similar seasons (July–October) and were selected on the grounds of being cloud-free. The spatial resolution is 80m (1975), 30m (1990, 2000, 2005 and 2009) and 15m (2015), which is sufficiently high for land-use analysis (Li *et al.*, 2009). The list of satellite data used in our study is given in Table II-1. Prior to visual interpretation, all satellite images were geometrically rectified by selecting ground control points and projected into Krasovsky_1940_Albers coordinates based on the 1:100,000 topography.

Auxiliary data was used to support the interpretation and validation of the land-cover classification, including the topographic map (1:100,000, 2000), vegetation maps (1:400,000, 1980), the geomorphic map (1:1 500,000, 2000), soil maps (1:1 500,000, 2000) and the water resources distribution map (1:1

500,000, 2000; http://www.resdc.cn). Atlases and maps of Inner Mongolia, climatic atlases of Inner Mongolia and other materials (e.g. ecological engineering maps) were used for visual interpretation to ensure the consistency and accuracy of data processing.

2.2.2 Visual interpretation and accuracy test

Computer-assisted visual interpretation of satellite images was chosen as the approach to map LUCC due to its high degree of accuracy (Liu *et al.*, 2005; Tong *et al.*, 2004). On-screen visual interpretation and digitalisation were performed on a fixed scale of 1:100,000. During interpretation, we adopted the following principles: (1) for the 1975 Landsat TM images, the minimum mapping patch was 4×4 pixels (equivalent to 240×240m on the ground) (Liu *et al.*, 2005); for the 1990, 2000, 2005 and 2009 Landsat TM/ETM+ images, the minimum mapping patch was 8×8 pixels (250×250m); for the 2015 Landsat OLI images, the minimum mapping patch was 16×16 pixels (250×250m); (2) the deviation of delineating locations was less than 1 pixels on screen. Interpreters used ARCGIS 9.2/10.2 software provided by ESRI to identify land-use types on screen, based on their understanding of object spectral reflectance, structure (texture, colour) and auxiliary information (Figure SI II-1). For more details, refer to Liu et al (2005). In 2000, 2005/2006, 2009 and 2015, several field surveys were carried out to evaluate classification accuracy from a total of 168 samples with photos geo-referenced using GPS facilities. The average accuracy of land-cover classification at the first level (Table II-1) of classification was 98.0%, and 86.5% at the subclass level (Table II-1).

Table II-1: Satellite data used in this study and corresponding ground-truthing references.

Time	Image sources			Sources	Number of field survey points	Accuracy	
	Sensors	Resolution [m]	Number			First class	Subclass
1975	MSS	80	40	https://www.usgs.gov/	____	____	____
1990	TM	30	35	https://www.usgs.gov/	____	____	____
2000	TM	30	35	https://www.usgs.gov/	72 (grassland only)	95.83%	84.72%
2005	TM	30	35	https://www.usgs.gov/	26 (grassland only)	100.00%	89.00%
2009	HJ-1	30	35	http://www.secmep.cn/secPortal/portal/indexLogin.faces	19 (grassland only)	100.00%	84.21%
2015	OLI	15	23	https://www.usgs.gov/	51 (32 points for grassland)	96.08%	88.23%

The classification used in this study was based on the 19 land-use types defined by Liu (2005), which were grouped into six aggregated classes of land cover: cropland, woodland, grassland, water bodies, unused land and built-up land (Table II-2).

Table II-2：Land-use types in Xilingol and their description.

1st level classes	2nd level classes	Description
Grassland	——	Land covered by herbaceous plants with coverage greater than 5%, including shrub rangeland and mixed rangeland with the coverage of shrub canopies less than 10%.
	Dense grass	Grassland with canopy coverage greater than 50%.
	Moderately dense grass	Grassland with canopy coverage between 20% and 5%
	Sparse grass	Grassland with canopy cover between 5% and 20%.
Cropland	——	Cultivated land for crops. Including: long-term cultivated land, newly cultivated land, fallow, shifting cultivated land; intercropping land such as crop-fruit, crop-mulberry and crop-forestry land in which a crop is a dominant species; bottomland and beach that has been cultivated for at least 3 years.
	Dry land	Cropland for cultivation without water supply and irrigating facilities; cropland that has water supply and irrigation facilities and planting dry farming crops; cropland planting vegetables; fallow land.
Woodland	——	Land where trees are grown, including arbor, shrub, bamboo and for forestry use.
	Forest	Natural or planted forests with canopy cover greater than 30%.
	Shrub	Land covered by trees less than 2 m high, canopy cover >40%.
	Woods	Land covered by trees with canopy cover between 10 and 30%.
	Others	Land such as tea gardens, orchards, groves and nurseries
Water body	——	Natural surface, natural water bodies or constructed reservoirs for irrigation and water reservation.
	Streams and rivers	Rivers, including canals
	Lakes	Natural lakes
	Reservoirs and ponds	Constructed reservoirs for water reservation and small natural ponds
	Permanent ice and snow	Land covered by perennial snowfields and glaciers.
	Beaches and shores	Land between high tide and low tide level.
Built-up land		Land used for urban and rural settlements, factories and transportation facilities.
	Urban built-up	Land used for urban settlements
	Rural settlements	Land used for village settlements.
	Others	Land used for factories, quarries, mining, oil-fields outside cities and land for roads and other transportation infrastructure
Unused land	——	Land that is not put into practical use or that is difficult to use.
	Sandy land	Sandy land covered with less than 5% vegetation cover
	Salina	Land with surface salt accumulation and sparse vegetation.
	Bare rock	Bare exposed rock with less than 5% vegetation cover.

2.3 Land use and cover change analysis

In this study, the patterns and processes of the overall LUCC between 1975 and 2015 were analysed by calculating the net change of land use and cover of the six classes (S), mapping the spatial patterns of losses and gains of the six classes. The net change was calculated using the following formula:

$$S = Sb - Sa \quad (1)$$

where *Sa* and *Sb* are the areas of the land-use type at the beginning and end of a period. In addition, we calculated a transition matrix for grassland to highlight changes between dense, moderately dense, and sparse grass and the respective land-use and land-cover classes. Changes in area over time from 1975 to 2015 were also identified in Table II-3.

In order to understand the effect of LUCC on environmental degradation and rehabilitation in Xilingol, following Zhang, Yu, Li, Zhou and Zhang (Zhang *et al.*, 2007), we redefined land degradation (LD), land restoration (LR) and land reclamation (R) based on the characteristics of land-use changes in Xilingol as follows:

LD: loss of grassland, water bodies and woodland due to transformation into cropland, built-up land and unused land. A decline in grassland coverage includes changes of dense grass into moderately dense grass and sparse grass, and of moderately dense grass into sparse grass.

LR: Expansion of grassland, water bodies and woodland due to transformation from unused land and cropland.

An improvement of grassland coverage includes moderately dense grass and spare grass changed into dense grass, and spare grass changed into moderately dense grass. This process is referred to as "revegetation" further below.

R: refers to unused land changed into cropland. In this paper, R is less than 0.01% of the total area, so it will be neglected here.

3 Results and discussion

3.1 Trend of LUCC since 1975

Over the past four decades, 6.7% (13,533.4 km^2) of the total area, including the six investigated land-use types, have undergone changes in Xilingol. Figure II-2 shows that the land-use type that increased most was the built-up area, which increased by 2339 km2 (1.2% of the total area) in the past forty years, followed by woodland, which increased by 439 km^2 (0.2% of the total). In contrast, water bodies and grassland areas decreased significantly in this period, shrinking by 1,694 km^2 (0.8%) and 1,072 km^2 (0.5%), respectively, in the study area. Cropland and unused land has changed a slightly, less than 0.1% of the total area. The results suggest that the area of land types with a higher ecological value (woodland, grassland and water bodies) is decreasing.

Land-use change can be divided into two distinct phases: 1975–2000 (Phase 1) and 2000–2015 (Phase 2) (see Table II-3 and Figure II-3). During Phase 1, there were four major land-use changes progressing as follows: cropland increase, a total of 1458 km2 dense grass changed into cropland in both periods

(1975-1990, 1990-2000). The cropland increase occurred mostly in the northeast of Xilingol (Figure II-3a). Built-up land expansion, mostly to the expense of grassland, occurred in the northeast more than in the southwest (Figure II-3a). Unused land expanded drastically in this phase, increasing by 534 km^2 and 1435 km^2 in these two periods, respectively. Here, grassland in the southwest was mainly affected. All in all, grassland decreased significantly: 2484 and 4212 km^2 were converted into other land-use types in the first phase, mainly in the southwest of Xilingol (Figure II-3b). Water bodies and woodland area changed only slightly during this phase.

During Phase 2, four entirely different land-use change processes were identified in Xilingol. While the cropland expansion was effectively contained in this period, the built-up land continued to expand, increasing by 1115 km^2, especially in the vicinity of the capital (Xilinhot) and northeast cities (Dongwuzhumuqin and Xiwuzhumuqin Banners; Figure II- 3c). Grassland mostly in the agro-pastoral transition zone (Zhenglan, Duolun, Taipusi Banner) and in sparse grass areas (Suniteyou Banner; Figure II- 3c). At the same time, grassland also continued to decrease in other areas, losing 5095 km^2, especially in Sunitezuo Banner (Figure II- 3d). Water bodies now showed a dramatic decrease in this phase, leaving unused land and dense grass areas behind (Table II-3). Such losses were mainly observed in the Dongwuzhumuqin Banner (Figure II-3d).

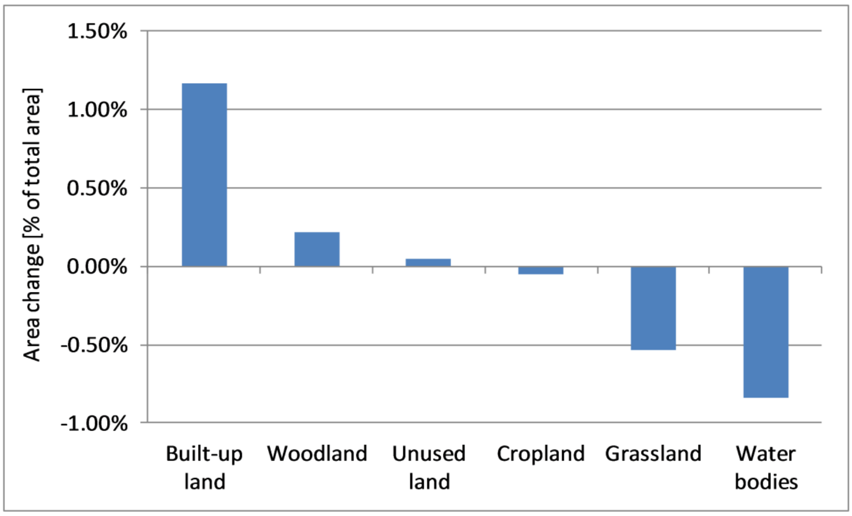

Figure II-2: The LUCC net change from 1975 to 2015.

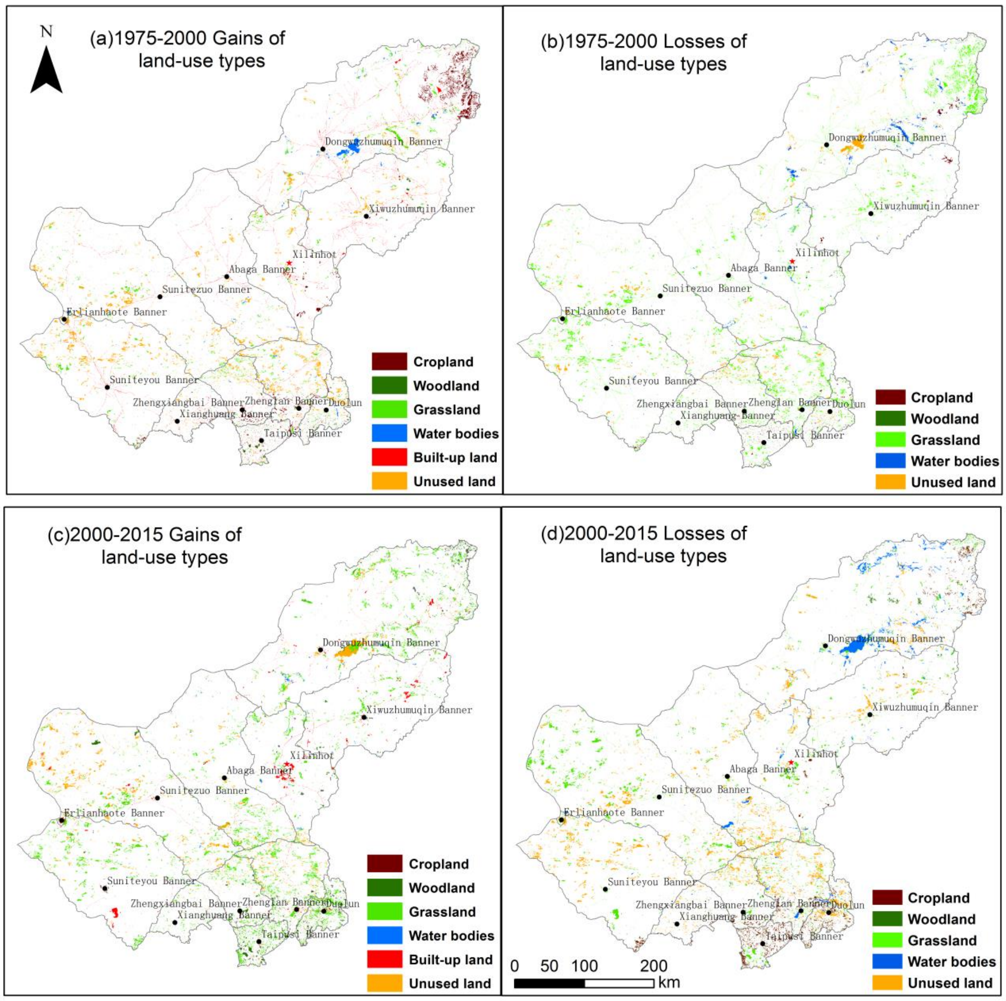

Figure II-3: The spatial pattern of land-use change in Xilingol (1975–2000,2000–2015), including gains (a, c) and losses (b,d) for specific land-use types.

Table II-3: Transition matrix of land-use and land-cover change in Xilingol from 1975 to 2015 (km2)

Period	Land-use type	Cropland	Woodland	Water bodies	Built-up land	Unused land	Dense grass	Moderately dense grass	Sparse grass	Losses
1975/ 1990	Cropland	3642.0	1.0	22.9	20.9	0.2	41.5	13.8	1.6	101.9
	Woodland	5.0	3860.5	0.0	8.6	0.0	0.5	0.0	0.0	14.1
	Water bodies	2.2	0.0	6152.0	14.7	213.6	31.0	10.4	8.4	280.3
	Built-up land	0.0	0.0	0.0	642.5	0.0	0.0	0.0	0.0	0
	Unused land	0.0	0.0	281.1	9.9	7912.6	34.7	89.4	175.9	591
	Dense grass	501.4	35.0	7.2	526.3	14.5	71805.7	2684.6	223.7	3992.7
	Moderately dense grass	32.2	0.9	6.3	347.3	143.0	859.6	72289.5	1553.3	2942.6
	Sparse grass	12.4	2.0	4.3	106.7	744.4	298.4	1122.2	24158.8	2290.4
	Gains	553.2	39.0	321.8	1034.4	1115.7	1265.8	3920.3	1962.9	
		Cropland	Woodland	Water bodies	Built-up land	Unused land	Dense grass	Moderately dense grass	Sparse grass	
	Cropland	3960.6	2.6	18.4	5.0	1.1	132.7	55.2	19.6	234.6
	Woodland	3.3	3844.0	0.0	0.1	0.0	45.6	6.5	0.0	55.5

1990/ 2000	Water bodies	10.5	0.1	5806.5	4.6	225.5	93.3	241.2	92.1	667.3
	Built-up land	0.0	0.0	0.0	1676.9	0.0	0.0	0.0	0.0	0
	Unused land	0.4	0.0	355.4	4.7	7449.3	36.1	399.7	782.5	1578.8
	Dense grass	956.3	104.1	42.3	85.5	77.9	64437.8	6602.2	765.3	8633.6
	Moderately dense grass	88.3	15.5	12.9	56.5	790.0	3472.3	65645.8	6128.3	10563.8
	Sparse grass	14.3	3.3	12.1	34.2	1918.3	818.3	3423.4	19897.8	6223.9
	Gains	1073.1	125.7	441.1	190.6	3012.8	4598.5	10728.1	7787.9	
		Cropland	Woodland	Water bodies	Built-up land	Unused land	Dense grass	Moderately dense grass	Sparse grass	
	Cropland	4585.8	10.5	1.8	21.6	2.9	283.4	98.7	29.0	447.9
2000/ 2005	Woodland	0.9	3885.8	0.1	0.6	0.0	76.0	4.2	2.1	83.9
	Water bodies	8.6	0.2	5122.4	4.1	827.3	143.1	80.1	61.9	1125.3
	Built-up land	0.0	0.0	0.0	1867.6	0.0	0.0	0.0	0.0	0
	Unused land	0.6	3.1	189.4	6.9	7133.4	176.2	992.5	1960.1	3328.8
	Dense grass	68.5	176.3	10.7	56.4	113.6	61390.5	6139.8	1080.4	7645.7
	Moderately dense grass	27.4	7.3	10.6	28.5	914.6	6672.7	63116.4	5596.4	13257.5
	Sparse grass	10.5	6.4	5.7	31.9	1477.7	1006.9	6045.9	19100.7	8585
	Gains	116.5	203.7	218.3	150.0	3336.1	8358.3	13361.3	8729.9	
		Cropland	Woodland	Water bodies	Built-up land	Unused land	Dense grass	Moderately dense grass	Sparse grass	
	Cropland	3985.6	8.0	0.0	2.6	0.1	609.9	91.8	4.3	716.7
	Woodland	0.2	3970.2	0.0	1.8	0.0	116.5	0.3	0.5	119.3
2005/ 2009	Water bodies	5.1	0.2	4693.3	2.4	209.2	227.6	131.7	71.2	647.4
	Built-up land	0.0	0.0	0.0	2017.6	0.0	0.0	0.0	0.0	0
	Unused land	0.4	0.0	102.6	6.4	8548.7	35.4	465.9	1310.1	1920.8
	Dense grass	63.1	13.5	5.9	59.9	27.8	67797.1	1616.0	165.6	1951.8
	Moderately dense grass	13.3	0.3	4.1	91.9	79.7	1934.6	73430.9	922.9	3046.8
	Sparse grass	2.4	0.3	3.5	35.9	397.4	229.7	2005.5	25155.9	2674.7
	Gains	84.5	22.2	116.1	200.9	714.2	3153.7	4311.1	2474.6	
		Cropland	Woodland	Water bodies	Built-up land	Unused land	Dense grass	Moderately dense grass	Sparse grass	
	Cropland	3605.9	37.0	0.0	20.2	0.1	347.4	47.3	12.2	464.2
	Woodland	0.2	3980.5	0.0	9.1	0.0	2.7	0.0	0.0	12
2009/ 2015	Water bodies	1.5	6.9	4545.1	25.0	53.3	136.1	22.2	19.2	264.2
	Built-up land	0.0	0.0	0.0	2218.5	0.0	0.0	0.0	0.0	0
	Unused land	0.1	13.3	121.2	23.7	8258.1	14.2	191.1	641.2	1004.8
	Dense grass	27.4	149.4	30.6	305.6	29.6	68352.7	1868.5	187.0	2598.1
	Moderately dense grass	8.9	105.6	26.1	285.2	140.3	2371.6	74233.8	570.6	3508.3
	Sparse grass	3.1	21.1	15.2	95.1	106.4	137.5	1276.9	25975.2	1655.3
	Gains	41.0	333.2	193.0	763.9	329.6	3009.4	3406.1	1430.3	

3.2 Grassland degradation and revegetation

Before 2000, the total area of grassland decreased by 2,077 km^2 (up to 1990) and 2,307 km^2 (up to

2000), where dense grassland was most affected (Figure II-4). Table II-3 indicates that most of the dense grass degraded to moderately dense grass in these two periods, leading to an increase in the area of moderately dense grass in this period. Meanwhile, moderately dense grass further degraded to sparse grass, and sparse grass was transformed into unused land, leading to an overall decrease in grassland coverage in this region. The trend of grassland degradation is also visible in the increase of grass yield losses. From 1985 to 1999, the average biomass production per hectare decreased from 509 kg to 320 kg (Akram *et al.*, 2009). During this period, grassland exhibited an overall trend of degradation. The resulting distribution map of grassland degradation and restoration presents spatial change patterns in Xilingol (Figure II-5). Grassland degradation includes two grassland conversion patters: grassland coverage decrease and grassland being converted into other land-use types. In Phase 1, grassland coverage decrease occurred in the capital city Xilinhot and the southwest of Xilingol. Grassland loss occurred across whole Xilingol. Xie and Sha (2012) have shown that degradation has a strong positive correlation with an increase in livestock density and human population. Overgrazing is considered to be the main cause of grassland degradation (Hao *et al.*, 2014).

In Phase 2 (2000–2015), grassland underwent rehabilitation. The total net area of grassland increased by 961 km^2 (up to 2005), 2,266 km^2 (up to 2009) and 84 km^2 (up to 2015; Figure II-4). Both dense grass and moderately dense grass tended to increase. This phase was characterised by an increase in area and coverage in this period, while the strongly degraded area decreased (Li *et al.*, 2012b). The grassland restoration includes two grassland conversion patterns: grassland restoration as the change of other land-use types into grassland, and grassland revegetation. Most of the grassland revegetation occurred around the capital city Xilinhot, and in the southwestern counties, in which moderately sparse grass areas dominated (Figure II-5). This trend of grassland revegetation is assumed a result of several grassland conservation projects and grassland protection strategies that have been established and implemented in this region (He *et al.*, 2017), including the "Returning farmland to forestland or grassland" project, the "Beijing and Tianjing sandstorm source control project", the "Sanbei shelter forest system construction" and the "Grassland desertification control project" (Hu *et al.*, 2013). The central aim of these projects was to improve rural environments and reduce livestock numbers (Briske *et al.*, 2015). Indeed, grassland areas increased and improved not only on the local scale, but also across the whole Mongolian Plateau. Mu et al. (2013) reported an obvious improvement of grassland in Inner Mongolia, which increased by 79,570 km^2 between 2000 and 2009. Li SY et al (2012b) stated that vegetation cover and biomass production improved from 2000 onwards in this region.

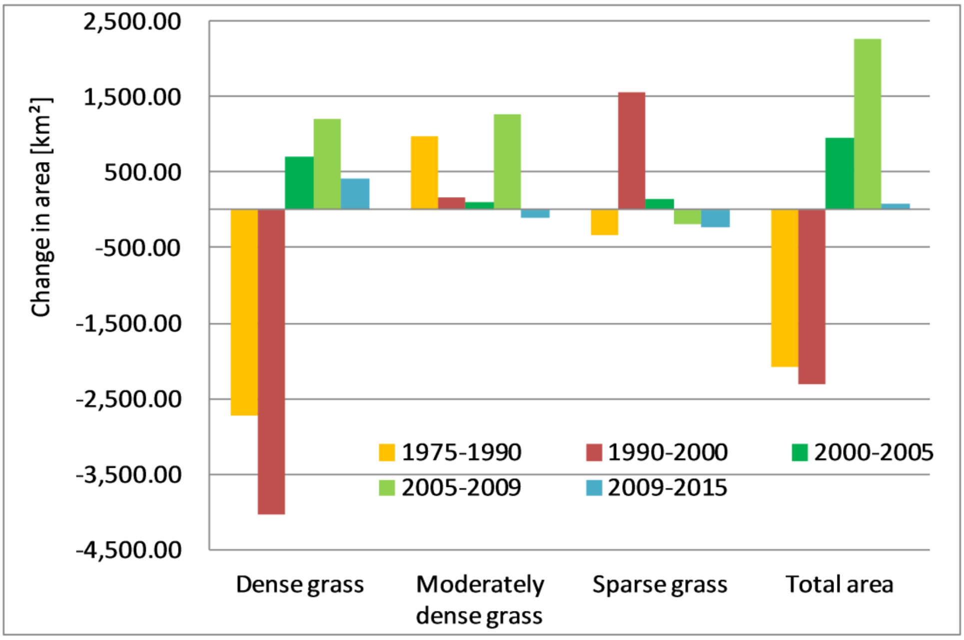

Figure II-4: Change in grassland density in Xilingol from 1975 to 2015.

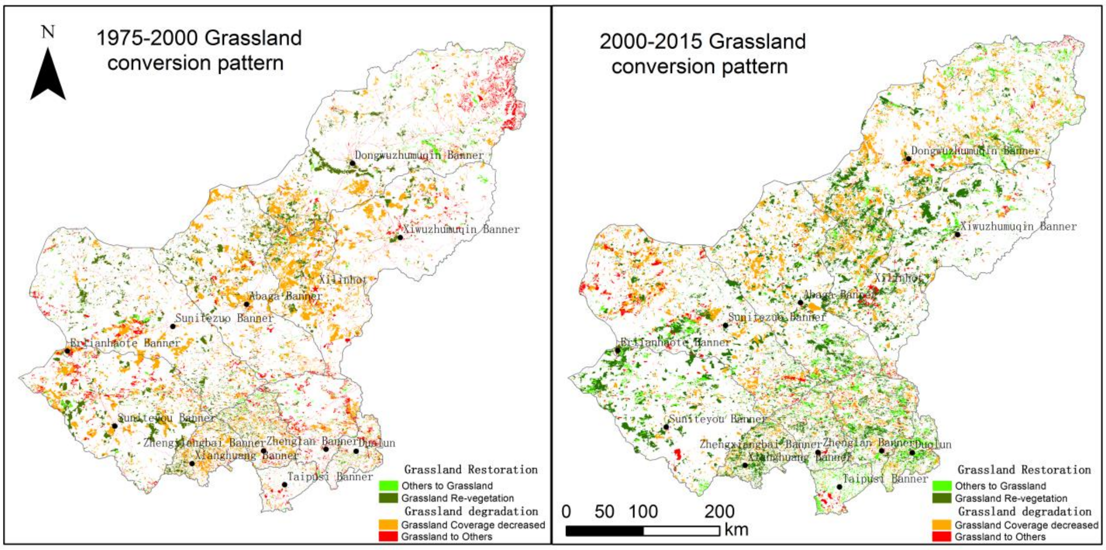

Figure II-5: Grassland degradation and revegetation in Xilingol (1975–2000, 2000-2015)

Although grassland has been restored over the past 15 years, significant damage continues to be visible. From 2000 to 2015, 953 km^2 built-up land (urban and rural areas, mineral mining, roads etc., Table II-3) and 2072 km^2 unused land evolved from grassland. After 2005, the mining industry grew into an important industry and development priority (Hu *et al.*, 2013). Coal mining is a petrochemical process that requires extremely large amounts of water and land. Mining causes the most dramatic and rapid land-use changes, affecting soil, groundwater aquifers and surface waters, due to the removal of top soil, excessive use of water, and the deposition of huge amounts of excavation material on the surface (Dai *et al.*, 2014). The development of the mining industry in Xilingol resulted in a large area of grassland being changed into coal-related industry infrastructure (e.g. roads), causing grassland fragmentation and accelerating grassland degradation (Qian *et al.*, 2014). As vegetation patches became more fragmented and homogeneous under grazing and urbanisation in Inner Mongolia (Lin *et al.*, 2010), species richness declined by 35% between 1968 and 2008 (McGovern *et al.*, 2011). Although numerous ecological projects have been implemented in Xilingol, it has not yet been possible to remedy the cause of grassland degradation (Akram *et al.*, 2009; Briske *et al.*, 2015). As long as economic development continues, with the growing population, overgrazing and mining pressure, grassland in Xilingol will degrade further and remain the most pressing ecological and environmental issue in this region.

3.3 Land degradation and restoration

In Phase 1 (1975-2000), the main land use process was land degradation (Figure II-6), with approximately 11.43% of the total area exhibiting a trend of degradation and only 5.39% of the total area land exhibiting a trend of restoration. Around 8.23% high coverage grassland changed into low coverage grassland. At the same time, in line with an increase in population and livestock, this process was characterised by cropland reclamation and sandy land expansion, the two land-use types that expanded as grassland declined sharply. Figure II-7 shows that the most obvious land degradation occurred in the east (Dongwuzhumuqin Banner, dominated by dense grass, which converted into cropland at large quantities), and around Xilinhot, followed by the west (Abaga, Suniteyou and Sunitezuo Banners) and the south (Xianghuang, Zhenglan, Xiwuzhumuqin, Zhengxiangbai, Erlianhaote, Duolun and Taipusi Banners) of Xilingol. The latter two regions were mostly dominated by moderately sparse grass, which turned into sparse grass or lost its vegetation cover completely.

In Phase 2 (2000-2015), the main land-use change process was land restoration, with land degradation still ongoing. A total of 12.0% of the area in Xilingol recovered during this phase, whereas 9.5% of the total area continued to degrade. Around 9.0% high coverage grassland developed from low coverage grassland, the revegetation annual change rate was 0.6% of total area, much higher than in Phase 1 (0.18%; Figure II-6). At the same time, around 7.5% high-coverage grassland changed into low-coverage grassland and 1.0% of unused land developed from grassland. In this phase, the east (Dongwuzhumuqin Banner) and west (Sunitezuo Banner) of Xilingol experienced both severe degradation and, to a lesser extent, also restoration at sites across the area, while the trend of degradation around Xilinhot was effectively curbed, with restoration rates exceeding degradation. A trend of restoration also dominated in the cropland and sandy land area south of Xilingol.

Figure II-6 shows that the land degradation/restoration rate also changed significantly between the two phases. During Phases 1 and 2, land recovered by 0.22% and 0.80% per year, respectively. However, land degradation in Phase 2 was 0.64% of the total area per year, which was faster than in Phase 1 (0.46%), making land degradation post-2000 an even more serious issue than pre-2000. All these results show that land degradation remains a major ecological and environmental issue in Xilingol. Water body area also decreased dramatically during Phase 2. Most water bodies were lost in the Donwuzhumuqin Banner, in which else dense grass converted into cropland and built-up land expanded. The latter suggests a direct correlation, where decreasing groundwater tables additionally affected the vegetation density.

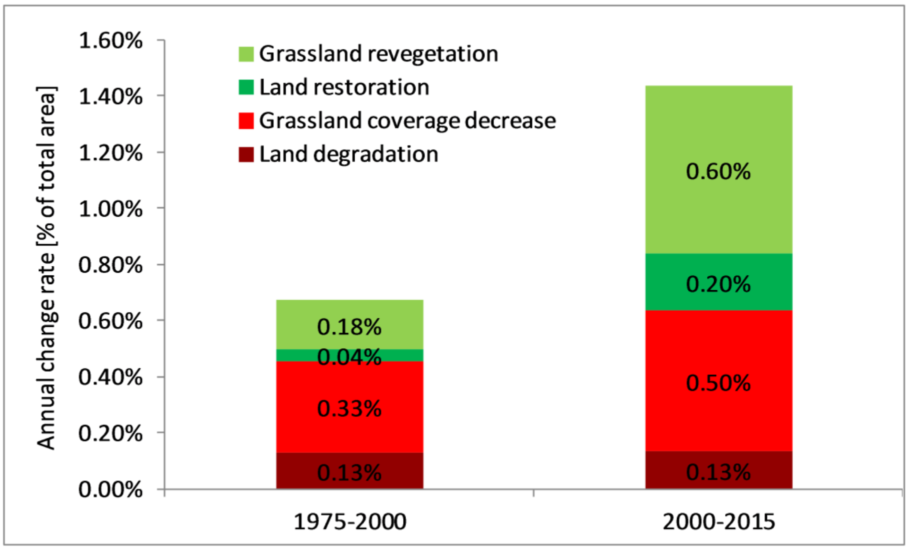

Figure II-6: Significant LUCC process rate in Xilingol from 1975 to 2015 as a percentage of total area.

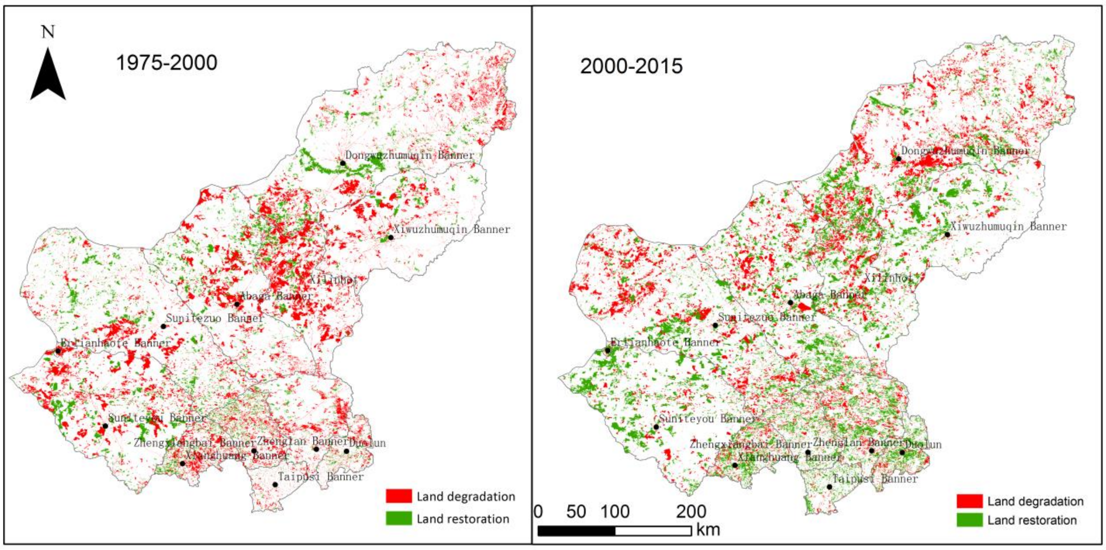

Figure II-7: Land degradation/restoration map in Xilingol for 1975–2015.

3.4 Policy frame

Drivers for the previously described observations of LUCC have not been analysed. Nevertheless, regional and national policy is supposed to have had a strong effect on the regional development in Xilingol, which is why we give at least a short overview of the most important policies here to better frame the observations. Overall, there have been four periods of area development strategies in Xilingol.

Under the "Cultural Revolution" before 1978, the government of Inner Mongolia set the goal of achieving self-sufficiency in food production in pastoral areas ("Take grain as the key link"). This policy resulted in a large-scale reclaim of grassland for food production in Phase 1.

In the second period (1978–1984), the Household Production Responsibility System "Price the livestock and assign to individual herders" program was fully implemented in this region to develop a stronger economy in Inner Mongolia. In this period, pastures were considered to be public spaces, and no property rights applied. Grassland remained largely unmanaged; the number of livestock is the only measure of economic development in Xilingol. Against this background, the number of livestock increased drastically, leading to grassland degradation and desertification. The "Pricing livestock, Herdsman possessing and raising" programme succeeded in promoting economic development in the short term. However, this development put additional pressure on grassland due to overgrazing, which was the main cause of grassland degradation between 1990 and 2000.

After 1984, the "Double Contract System" (Sai, 2014) linked the responsibility, rights and benefits of grassland management directly to herders (Li *et al.*, 2014b), combining husbandry operation and grassland management. As a consequence, grassland was no longer a free-to-use public good. After 1996, in a bid to improve stock rating and grassland quality, the "Two rights, one system" programme (referring to the separation of land-owner and land-user rights) (Sai, 2014) followed, which included an improved ownership, tenure and contract responsibility system. However, this policy boosted herders' confidence and stimulated husbandry breeding. The "Two rights, one system" programme lasted until 2005. HPRS, which had been designed to raise herders' awareness of protecting and maintaining productive grassland, was then introduced.

Around 2000, as a response to the increasing occurrence of sandstorms and flooding, the Chinese government initiated a number of ecological engineering projects intended to strengthen environmental protection. The most famous strategy, Fencing Grassland and Moving Users (FGMU), was enforced in 2002 with the aim of moving people away from degraded grassland areas by changing the mode of livestock production (e.g. encouraging herders to breed dairy cows instead of sheep) and business operation to improve the environment and increase the herders' incomes (Akram *et al.*, 2009). As a result of the new institutional arrangements (fencing and grazing exclusion), stock rating decreased significantly after 2000, which had a significantly positive effect on vegetation conditions (Huang *et al.*, 2009b), but a negative effect on herders' livelihoods (increases in the cost of livestock production and decreases in the net income of herders) (Uthes *et al.*, 2010b).

In 2005, the Chinese government exempted agriculture taxes, while the local Xilingol government began to focus on its rich mineral resources. In the most recent period, the economic development pattern has changed from traditional nomadic husbandry to an industry-dominated pattern, with visible consequences for land-use and grassland quality.

Effects of the issued polices on land-use change dynamics suggest themselves, but are not subject of this paper. A more elaborated driver analysis will follow.

4 Conclusion

LUCC analysis reveals that human land use has increased considerably in recent decades. Land degradation, especially grassland degradation, remains a major ecological problem in this region. Land-use management strategies and grassland conservation strategies have had a significant influence on LUCC in the past forty years, especially for cropland, grassland and unused land. Since the 1970s, irrational land-use policies have caused around 11.4% of the total area to experience land degradation; after 2000, land degradation increased by 9.5%. Grassland degradation, the key land degradation process in Xilingol, exhibited a positive trend after 2000 (Li *et al.*, 2017b; Tao *et al.*, 2015a). Previous research showed that degraded grassland can recover under grazing ban conditions (Jiang *et al.*, 2006). Different degrees of implementation of grassland bans have been launched in Inner Mongolia since 2002: full grazing bans on severely-degraded grassland, keeping moderately-degraded grassland fallow, initiating grazing rotation on slightly degraded grassland and rearing livestock in sheds (Dong *et al.*, 2007).Yu and Farrell (2016) stated that in 2014, compared with non-banned area, the vegetation coverage, average vegetation height, and fresh grass yield were all higher in banned area by 6%, 53.6% and 30.8%, respectively; some land-use types that had previously changed from grassland have the potential to recover and develop back to original grassland (Andrade *et al.*, 2015). All these findings suggest that grassland degradation can be reversed under sustainable grassland conservation strategies. Although policy-driven ecological projects in Xilingol seem to have improved environmental conditions to some extent, the government also invested heavily in herders. However, it seems that these projects will continue to be unable to fully resolve the livestock-related environmental and social problems (Li *et al.*, 2014b). It is evident that current subsidies are still not enough to ensure the sustainable livelihood of herders (Li *et al.*, 2014b). It is also very likely that – due to the temporary nature of most ecological projects – subsidies will be discontinued as soon as the environment has recovered to some extent. Once this happens, herders will again be at risk of falling into poverty, with the known consequences for the environment . So far, ecological projects have managed to restore the environment, but have failed to pay sufficient attention to herders' livelihoods, society and culture (Li *et al.*, 2014b). The development of the mining industry and continuing population growth have placed an even greater pressure on livestock since 2005, putting the grassland ecosystem in Xilingol to a severe test. The mining industry has become an important industry in Xilingol, but grassland remains important to societal and cultural identity in the region. Sustainable grassland management under the new economic development should remain high on the political agenda. To support this, future research needs to explore in greater detail the driving factors of the observed processes and patterns, enabling us to better understand and predict possible future developments.

Acknowledgements

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Supplementary Information

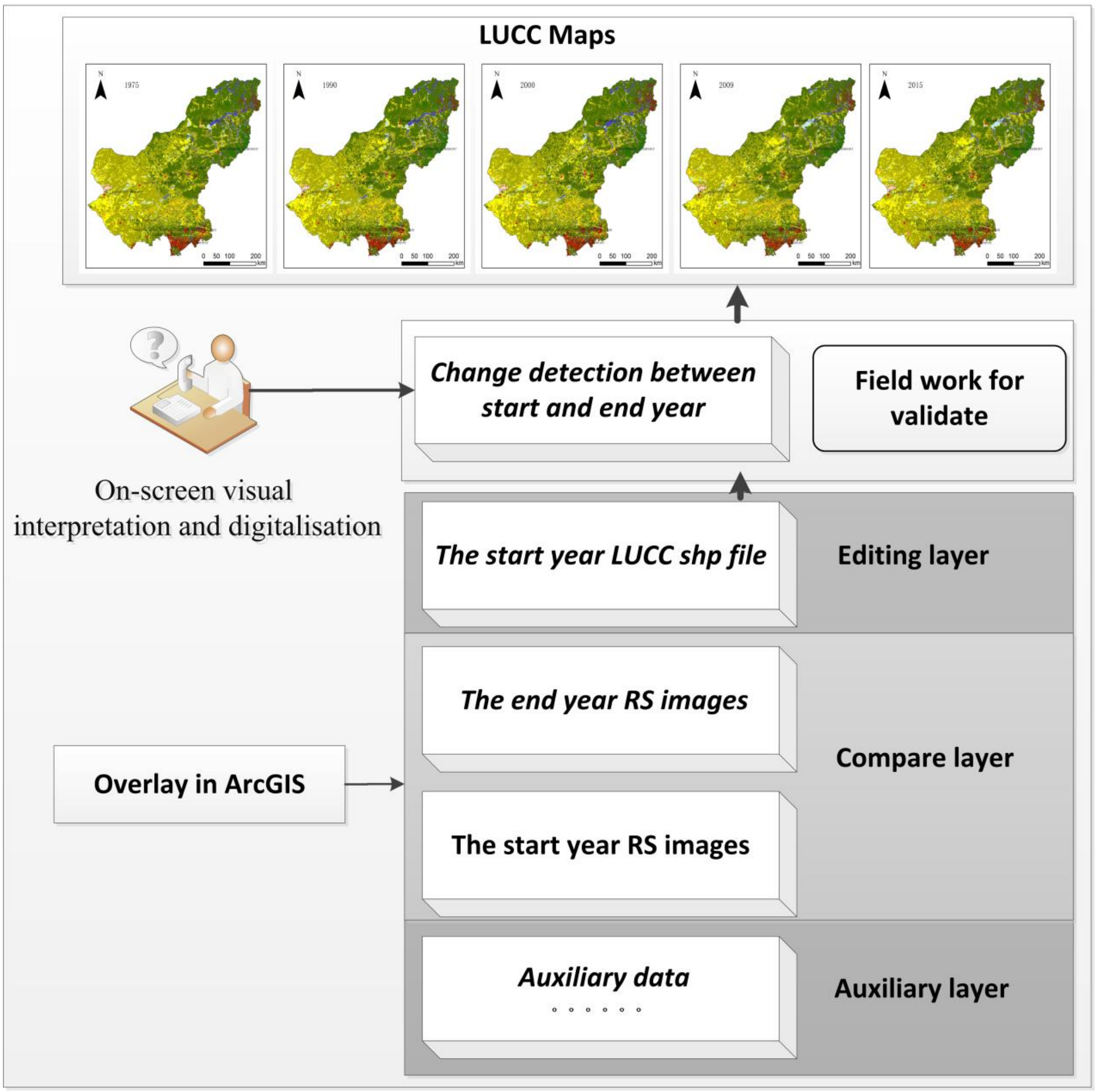

Figure SI II-1: Visual-interpretation process

Chapter III:
Identifying drivers of land degradation in Xilingol, China, between 1975 and 2015

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Abstract

Land degradation occurs in all kinds of landscapes over the world, but the drivers of land degradation vary from region to region. Identifying these drivers at the appropriate spatial scale is an essential prerequisite for developing and implementing appropriate area-specific policies. In this study, we investigate nine different driving factors in three categories: human disturbance, water condition, and urbanisation. Using partial order theory and the Hasse diagram technique, we analyse the temporal and spatial dynamics of these drivers and identify the major drivers of land degradation at the county level in the Xilingol League, China. Our findings indicate that: (i) in eight out of the region's 12 counties, human disturbance was the dominant driver responsible for land degradation up to 2000, followed by water conditions, while urbanisation was the dominant driver in only four counties; (ii) the effects resulting from human disturbance and water availability decreased after 2000, while urbanisation became the dominant driver for land degradation in seven counties. The influence of human disturbance in this region has decreased, which suggests that ecological protection policies that were designed to control population and livestock numbers have worked as intended for this region. However, land degradation has continued and new policy measures are required to ease the effect of urbanisation.

1 Introduction

Land degradation (LD) is a global problem that is closely connected with threats to food and energy security, a decline in standards of living, and the loss of biodiversity (Reed *et al.*, 2011). The phenomenon has been defined as any loss of soil quality, productivity, biodiversity, standards of living, or the provision of other ecosystem goods and services, ranging from slight decline to complete destruction or transition into different land uses (Lambin *et al.*, 2003). Most severe cases are associated with arid, semi-arid and dry sub-humid zones, which together cover about 47% of the earth's terrestrial surface (Gisladottir & Stocking, 2005). Closely interwoven with climate change, LD has given rise to a multitude of national and international policy responses.

Understanding the drivers of LD is crucial for the development of policies and measures that aim to turn current trends towards more socially and environmentally friendly outcomes. The drivers of LD are numerous and complex, and they vary across regions. Climate change, economic and technological development, cultural habits and political contexts have all been identified as important drivers in LD processes (Kirui, 2016; Reed *et al.*, 2011). However, data on drivers concerning land use changes are scarce, which is why most of the recent analyses look at these drivers as if they were static (Deng *et al.*, 2011; Gollnow *et al.*, 2018). In light of the idea that LD is a dynamic process (Batunacun *et al.*, 2018), the drivers themselves should also be considered according to their temporal and spatial dynamics.

Due to its fragile grassland ecosystems, the arid to semi-arid area of the Xilingol League, located in Inner Mongolia, China, makes an excellent case study for researching LD. Furthermore, Xilingol has been subject to the entire range of China's grassland policies. Climate and human disturbance have been found to be the major driving forces for grassland degradation in this area (Hu *et al.*, 2015; Sun *et al.*, 2017); urban as well as rural development came at the expense of much of the grassland in this area, especially after 2000 (Batunacun *et al.*, 2018). Road construction and mining development not only destroyed grassland, but also fragmented the remaining grassland area and consumed significant amounts of groundwater resources (Deng *et al.*, 2011; Tao *et al.*, 2015a). In our present study, we collected nine potential drivers of land use changes, and analysed data from 1975, 2000 and 2015, to unveil the relationship between these drivers and LD. The nine drivers include the human population density, livestock density, the presence of urban structures, activities by rural settlers, road construction, mining, the presence of water bodies and two climate factors (temperature and precipitation).

In a bid to explore the drivers' relation to LD, numerous methodologies have been used in previous studies. For example, statistical models (e.g. logistic regression, principal component analysis) have been employed to unveil the statistical relationships between various drivers and grassland degradation (Gao *et al.*, 2015; Lin *et al.*, 2014). Scenario analysis using land use models (e.g. the CLUE-S model, see (Verburg *et al.*, 2002) were based on socioeconomic or biophysical drivers (Li *et al.*, 2012b), while factors associated with deforestation and degradation have been identified using machine-learning algorithms (Dlamini, 2016). Geist & Lambin (2002) and Kirui (2016) have summarised possible drivers of LD in literature reviews. A rich body of studies also exists that has investigated the relationship between drivers and LD, both quantitatively and qualitatively. However, the same causal drivers can lead to diverging consequences in different contexts because of their varying interactions with other proximate and underlying causes of LD (Kirui, 2016). For this reason, it is necessary to use all available driver information separately, instead of merging them into one composite indicator, and to rank and compare LD drivers to provide decision-makers with effective information to derive adjustments to current ecological policies. The concept of Partial Order Ranking (POR) has been identified as one tool that can fill this gap; POR has been shown to be useful in environmental science when sets of qualitative indicators need to be compared and evaluated (El-Basil, 2006). Moreover, the Hasse Diagram Technique (HDT) helps to diagram partial order relations of all objects in such a set (Wieland & Bruggemann, 2013).

The partial order theory has been used in many studies, e.g. in risk assessments of chemicals (Bruggemann & Voigt, 2012), ecosystem service comparisons (Tsonkova *et al.*, 2015) and water quality assessments (Simon *et al.*, 2006). In this study, we utilise POR as a useful tool to analyse drivers of LD with the aim of adjusting land use management strategies at the county level. The objective of this study is therefore to use POR to (1) analyse temporal and spatial LD driver dynamics in Xilingol; (2) compare and rank the LD drivers at the county level; and (3) summarise the ecological policies and measures that were initiated in Xilingol between 1980 and 2020 as well as to discuss possible policy measures for the future.

2 Data and methods

2.1 Study area

The Xilingol League is located in the centre of Inner Mongolia, spanning from 41.4°N to 46.6°N and from 111.1°E to 119.7°E (Figure III-1) and covering an area of 206,000 km^2. The mean annual temperature in Xilingol (1958–2015) was 2.2 °C and the mean annual precipitation was 278 mm. Its population has grown to 1.044 million people as of 2015, of which around 37% live in the rural parts of the league. About 87% of the land is covered with grassland, which is subject to livestock grazing. Animal husbandry had long been the major industry, and is still significant; livestock has principally consisted of sheep, goats and cattle, which produce dairy products and wool, especially cashmere. Xilingol is also rich in mineral resources, such as coal, oil, copper, gold, and many other nonferrous metals. Since 2008, the mining industry has emerged as the dominant economic sector, making animal husbandry the second-most important source of income (Yang Y *et al.*, 2011). Xilingol has fertile grassland in northern China, but sandstorms have increased in recent decades (Mang-Mang Gou *et al.*, 2010). In light of this, a combination of different ecological policies has been launched to combat ecological issues.

There are a total of twelve counties in Xilingol: two municipalities (XL: Xilinhot, EL: Erlianhot), nine banners (an administrative unit equivalent to a county, DW: Dongwuzhumuqin, XW: Xiwuzhumuqin, AB: Abaga, SZ: Sunitezuo, SY: Suniteyou, XH: Xianghuang, ZXB: Zhengxiangbai, ZL: Zhenglan, TP: Taipusi) and one county (DL: Duolun; Figure III-1). The county/banner is the third level in China's administrative hierarchy, below provinces and prefectures. Since the counties possess their own administrative government, we choose the county (or banner or municipality) as our unit of analysis, given that we seek to target county governments with our suggestions for creating or improving their regional land use plans (Deng *et al.*, 2008).

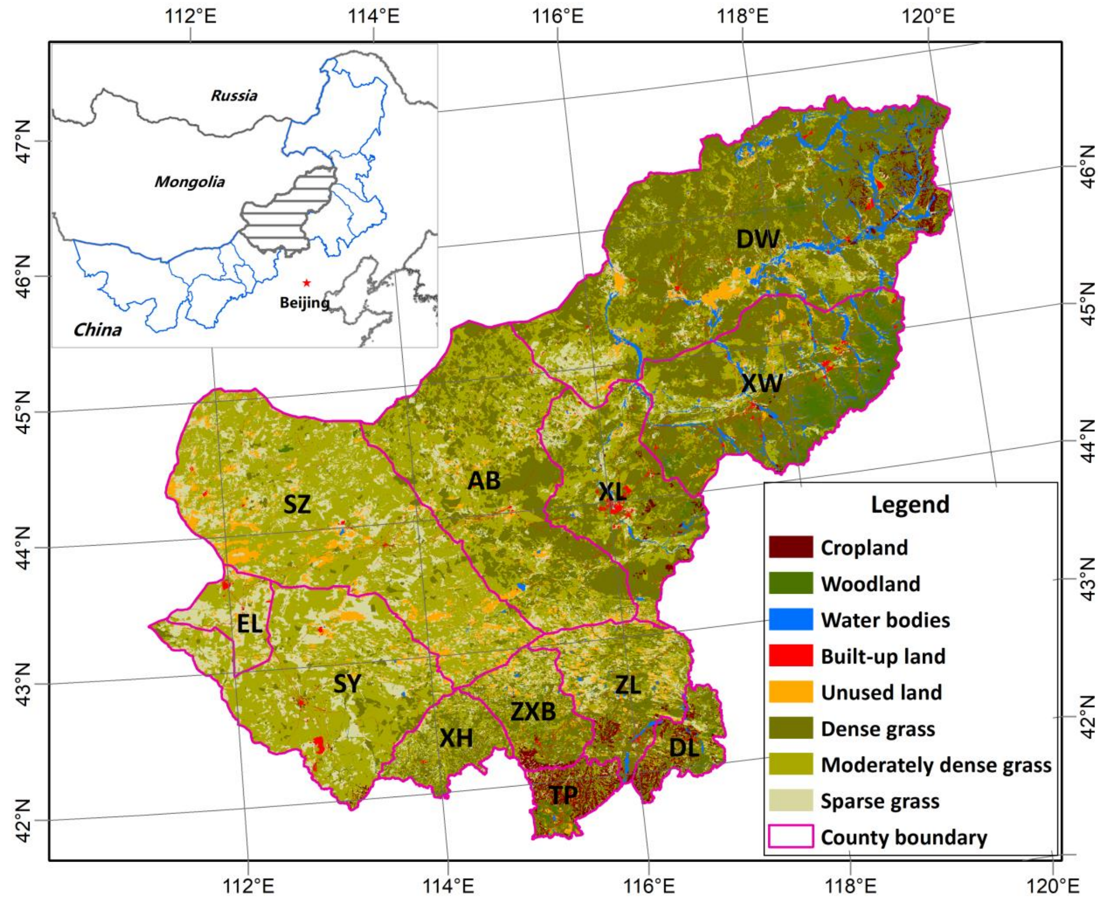


Figure III-1: Land use / land cover (2015) in Xilingol.
Note: DW, Dongwuzhumuqin; XW, Xiwuzhumuqin; XL, Xilinhot; AB, Abaga; SZ, Sunitezuo; SY, Suniteyou; EL, Erlianhot; XH, Xianghuang; ZXB, Zhengxiangbai; ZL, Zhenglan; DL, Duolun; TP, Taipusi.

2.2 Land degradation data and processing

This study defines LD based on land use conversion, such as the loss of grassland, water bodies and woodland due to transformation into cropland, land development, and unused land (land that is not put into practical use or that is difficult to use), while grassland degradation is referred to as a decline in grassland coverage (Batunacun *et al.*, 2018). We analysed LD based on a land use and land cover change (LUCC) analysis in a previous study (Batunacun *et al.*, 2018). The results indicate that two distinct phases emerge: during Phase 1 (1975–2000), 11.4% (22,937 km^2) of the total area degraded, of which grassland degradation accounted for 8.2%. During Phase 2 (2000–2015), a further 9.5% (19,124 km^2) degraded, including 7.5% for grassland degradation. However, the comparison of the two periods revealed that the degradation rate has further increased (from 0.46% of total area annually to 0.64%(Batunacun *et al.*, 2018), and that LD continues to be the main ecological issue in Xilingol (Batunacun *et al.*, 2018). In order to assess which drivers were probably responsible for the LUCC observed, we processed all LD data in a 1×1 km^2 grid using ArcGIS, creating a total of 22,579 pixels in Phase 1 and 19,140 pixels in Phase 2 (Figure III-2).

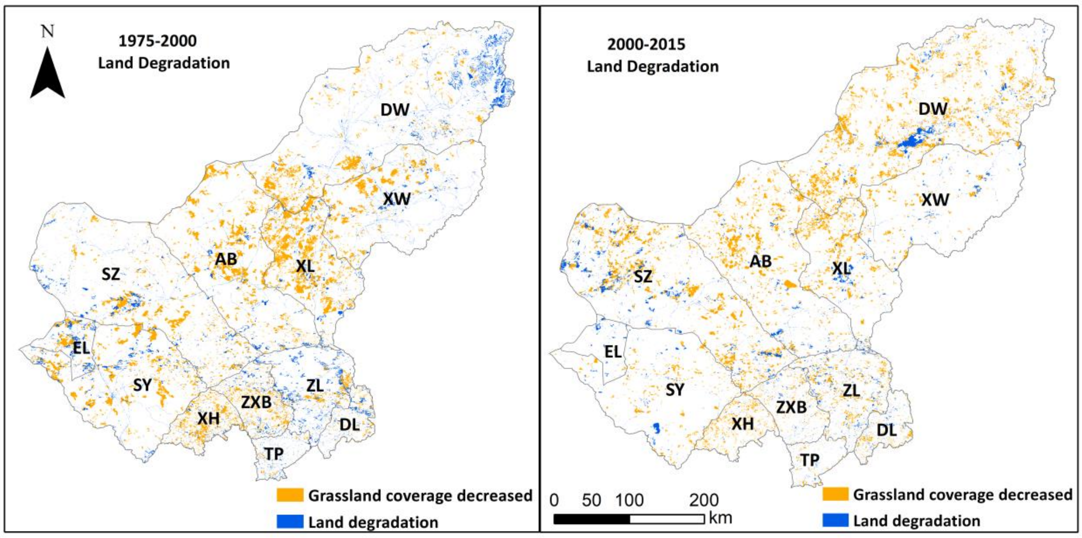


Figure III-2: Land degradation in two phases: 1975–2000 (left) and 2000–2015 (right).

2.3 Identifying possible drivers

This study began by compiling a list of possible drivers of land degradation (Geist & Lambin, 2002; Mirzabaev *et al.*, 2016) and grassland degradation (Li *et al.*, 2012b) from previous literature. Nine independent variables were created to account for drivers of land degradation: the distance to the nearest urban centre (hereafter referred to as "urban"), the distance to the nearest rural settlement ("rural") , the distance to the nearest road ("roads"), the distance to the nearest mining area ("mining"), the distance to the nearest surface water body ("water bodies"), the human population density ("population"), the livestock density ("livestock"), the mean growing season temperature ("temperature") and the annual sum of precipitation ("precipitation"). In an attempt to ensure consistency with the LD process, we collected all variables at three distinct points in time: 1975, 2000 and 2015 (livestock data were not available for 1975, so we used livestock data from 1978 in this study; Table III-1: Driver definitions and derivations). Climate factors were extracted from the longest available weather data set and, to reflect the fact that grassland is more sensitive to the growing season (April to Sep), we used the average growing season temperature (1958–2015; Table III-1: Driver definitions and derivations). We grouped all variables into three categories: "human disturbance", represented by population and by livestock density; "water conditions", represented by the distance to the nearest water body, by temperature (as a proxy for evapotranspiration) and by precipitation; and "urbanisation/industrialisation", which includes distances to urban centres and rural settlements, to roads, and to mines (from here on, we refer to this group as "urbanisation" for the sake of simplicity). A study by Li et al. (2012a) previously identified increases in human population and in the number of livestock as the major driver of grassland degradation in Xilingol. Surface water bodies, precipitation and temperature have an important effect on soil moisture, and vegetation in the arid and semi-arid area of Xilingol responds very sensitively to changes in water conditions, especially to the drying out of surface waters (Fan *et al.*, 2010; Tao *et al.*, 2015a). Furthermore, urbanisation, road construction, and the establishment and development of mines have consumed much of the grassland area, leading to grassland area fragmentation and degradation (Batunacun *et al.*, 2018; Qian *et al.*, 2014; Tao *et al.*, 2015a).

We used different measures to quantify these drivers (D). Based on the 1×1 km^2 grid cell for both phases of LD, we defined the following drivers using the following methods: (1) We used ArcGIS to determine the Euclidean distance (Lin *et al.*, 2014) from an LD pixel to corresponding water bodies, urban areas, rural settlements, roads and mines. (2) We processed the human population data into density data for the three time points (1975, 2000, 2015, see Table III-1), and we converted all livestock into sheep units for every grassland pixel for the three points in time. (3) For daily temperature and precipitation data, in combination with elevation data, we used a Kriging interpolation algorithm (Nalder & Wein, 1998) to produce the 1×1 km^2 raster data via Python, and then extracted all grid cells with LD attributes.

Table III-1: Driver definitions and derivations

Driver processes and orientation									
Categories of all drivers	Urbanisation/industrialisation				Water conditions			Human disturbance	
Driver name	Urban	Rural	Road	Mining	Water body	Temperature	Precipitation	Population	Livestock
Time series	1975, 2000, 2015				1975, 2000, 2015	Daily data from 1958 to 2015		1975/1978, 2000, 2015	
Data sources	Remote sensing images (Landsat MSS/TM/ETM*)					China Meteorological Bureau		Inner Mongolia Statistical Yearbook	
Measures	Distance measures				Distance measures	Average temperature from April to September	Annual precipitation	Population density	Sheep unit density only for grassland
Driver abbreviations	Distance to urban: Durban1975, Durban2000, Durban2015 Same as distance to rural, road, mining				Distance to water body: Dwater1975 Dwater2000 Dwater2015	T1958-2000 T2000-2015	P1958-2000 P2000-2015	1975popD 2000popD 2015popD	1978sheepD 2000sheepD 2015sheepD
Description	The Euclidean distance from the land degradation object to the driver object				The Euclidean distance from the land degradation object to the closest water body	Kriging to produce a temperature and precipitation value for every land degradation object		Calculation of population and sheep unit density for every land degradation object.	
Unit	km				km	℃	mm	person/km^2	sheep unit/km^2
Normalised process	Normalising drivers to [0,1]								
Orientation (the definition	The closer to urban or rural centres, roads or mines, the higher the pressure for grassland				The further away from surface waters, the more	With higher temperatures, more soil water is	With lower precipitation, less water is	The higher the density of inhabitants or livestock, the more intense land use is. From the smallest to the largest value, the	

is stated below)	overuse or use change is. From the smallest to the largest value, the corresponding normalised value is [1, 0]	easily degrading occurs. From the smallest to the largest value, the corresponding normalised value is [0, 1].	lost through evaporation. From the smallest to the largest value, the corresponding normalised value is [0, 1].	available to sustain grass growth. From the smallest to the largest value, the corresponding normalised value is [1, 0].	corresponding normalised value is [0, 1].

*MSS: Multi Spectral Scanner (Landsat 1-7), TM: Thematic Mapper (Landsat 4, 5), ETM: Enhanced Thematic Mapper (Landsat 7).

2.4 Partial order ranking and the Hasse diagram technique

2.4.1 Partial order ranking theory

Partial order theory allows researchers to conceptualise comparison of elements, especially if they possess more than one indicator. Partial ordering also enables all information about the objects to be maintained (Brüggemann & Carlsen, 2006). In the present study, POR has been used to rank the drivers of land degradation in Xilingol, followed by a comparison of the ranking results for the two periods (P1: 1975–2000, P2: 2000–2015).

Given a set of objects, X={a, b, c…}, objects a, b, c, etc., are compared with each other. Therefore, in this study, X refers to counties, and a, b, c denotes the individual county or banner. For a partial order, the following axioms are valid (Hilckmann *et al.*, 2017).

(1) (Reflexivity): $a \leq a$, for all $a \in X$;

(2) (Transitivity): If $a \leq b$ and $b \leq c$, then $a \leq c$, for all $a, b, c \in X$;

(3) (Antisymmetry): If $a \leq b$ and $b \leq a$, then $a = b$, for all $a, b \in X$.

In the study presented here, elements and objects both refer to counties. Here, the "element" refers to the theoretical concept, whereas "objects" are used as the generalisation for the counties/banners of Xilingol.

2.4.2 The Hasse Diagram Technique (HDT)

A Hasse diagram is a visual representation of partial order relations among objects described by a number of indicators; let X be the finite set of objects and IB the set of indicators q_i, (i=1,…,|IB|). The objects and their indicators are called "partially ordered sets" (posets). Posets can be described as a data matrix Q (N×R) containing N objects and R variables or indicators (Voyslavov *et al.*, 2013). In this study, objects have been described as land degradation in twelve counties in two phases (P1 and P2); these objects were denoted as Counties_P1 and Counties_P2, and a total of nine indicators were grouped into three categories (see Table III-2). The three categories with their three points in time were denoted as IB_human_P1, IB_water_P1, IB_urban_P1, and IB_human_P2, IB_water_P2, IB_urban_P2. Ultimately, six posets were produced: (Counties_P1, IB_human_P1), (Counties_P1, IB_water_P1), (Counties_P1, IB_urban_P1), (Counties_P2, IB_human_00_15), (Counties_P2, IB_Water_P2), (Counties_P2, IB_urban_P2). Accordingly, six Hasse diagrams were produced for the available data.

In the present study, the comparison of the counties/banners, characterised by LD drivers, can be explained as follows:

$$\begin{cases} x \geq y & \text{<=>} \quad qi(x) \geq qi(y) \quad \forall \quad qi \in IB \\ x \leq y & \text{<=>} \quad qi(x) \leq qi(y) \quad \forall \quad qi \in IB \\ x \| y & \text{else} \end{cases} \qquad (3)$$

When $x \geq y$ or $x \leq y$, county x and y are comparable; when $x \| y$, county x and y are incomparable.

In a Hasse diagram, a set of objects in the same vertical position is called a “level”. “Chains” indicate a sequence of totally ordered elements, in which no incomparability exists. Chains can be used to trace the dominant drivers of LD with regard to the input data. A maximal element is one that has no other element further above, and it is usually drawn at the uppermost level of the diagram. A minimal element has no other element further below, and it is usually positioned at the lowest point of the diagram (see 2.3.3 and Figure III-3). An element $x \in X$ that is not comparable to any other element and that simultaneously fulfils the definition of both a maximal element and a minimal element is called an isolated element (Hilckmann *et al.*, 2017; Tsonkova *et al.*, 2015; Voyslavov *et al.*, 2013). In this study, the maximal element indicates a driver that had a dominant effect on LD in the county (large values for driver attributes), and the minimal element indicates that the driver has little influence on LD (small values for driver attributes). Isolated elements are not comparable with any other elements.

Before applying POR, all indicators have to be “normalised” and then “oriented”. All indicators have to be normalised to the [0, 1] scale by using Equation (4) (Tsonkova *et al.*, 2015):

$$qn_i(x) = \frac{q_i(x) - q_i min}{q_i max - q_i min} \qquad (4)$$

qn_i is the value of the indicator; $q_i max$ and $q_i mim$ are the maximum and minimum values of the respective indicator.

Since not all indicators contribute equally to the aim of the ranking, it is crucial to consider the orientation of all indicators before they are ranked. This also creates a conceptual link between the (normalised) values and the actual effect for each driver. The orientation of all the drivers is listed in Table III-1. For the human disturbance group drivers, the effects of population and livestock increase with the growth of population and increasing livestock density. For the water condition group drivers, the effects of temperature increase with temperature, while the water body effects increase as distance from the water bodies increases, and the effects of precipitation decrease as precipitation increases. One could argue that surface water bodies attract livestock and would then foster grassland degradation, but this degradation occurs only at a very small scale, and on surfaces also closely related to mining development in Inner Mongolia (Li *et al.*, 2012b; Tao *et al.*, 2015a). For the urbanisation/industrialisation group, the effects of the four drivers decrease with distance. We are aware that rural-urban migration, as an important urbanisation process, can also indirectly show positive effects on LD, e.g. people leaving the grassland areas to move to urban areas, seeking better social conditions. However, this effect is difficult to measure, in contrast to the negative, direct effects. Also, when rural people move to urban areas, the individual grassland properties are not always completely abandoned. Landholders rent out the grassland, which is continuously used for grazing. In a bid to keep in line with other previous studies (Wang *et al.*, 2017), we retain the interpretation of urbanisation as a negative effect. Since we now have a group of drivers which increase with the measure and another group that decrease with the measure (distance to urban land, rural settlement, road, mining and precipitation), we need to harmonise the two groups. For this purpose, we inverted the latter group as $qin_i(x) = 1 - qn_i(x)$ (see Figure SI III-1).

This study classifies orientation as either "strong" or "weak", where "strong" indicates that the driver has a strong effect on the LD process (strong objects are located in the upper levels of an HD), while "weak" indicates that the driver has a small impact on LD (weak objects are located in the lower levels). In the normalised value space between 0 and 1, 0 indicates the weakest possible effect, and 1 the strongest.

2.4.3 An example of a Hasse diagram application in this study

As an example, Figure III- 1 shows how the HDT is used in this study. We extracted urbanisation data from the 2000–2015 period for five counties and analysed the eight selected indicators (distance to urban centres, rural settlements, roads and mining areas for the two phases) simultaneously (Figure III-3, left). Each county is represented by a circle, and the relationships between different counties are represented by lines with an arrow. XH and DW are located in Level 1 with the largest value of all eight indicators, which means that LD in both counties is significantly close to these four drivers and affected by urbanisation. SZ is located in Level 3, with smaller values of these indicators, with points at no effect through urbanisation. Three levels are visible in this example.

EL is an isolated element. With the lowest value of distance to rural areas in 2000 (Drural_2000), no comparability exists with other counties (Figure III-3, in red). In addition, a total of five chains are present in this example: (DW, AB, SZ), (XH, AB, SZ), (DW, AB), (XH, AB) and (AB, SZ). These chains indicate an existing comparison of the urbanisation effects for the respective counties. All indicators are ordered weakly (all indicators sorted from the largest to the smallest value) along this chain (from bottom to top). All in all, in this example, urbanisation is the major driver in XH and DW, while the impact of urbanisation in EL is not shown clearly. The HDT was implemented using Python (Wieland, 2018).

The input data of HDT

2000-2015 Urbanisation indicators								
County Name	Durban 2000	Drural 2000	Droad 2000	Dmine 2000	Durban 2015	Drural 2015	Droad 2015	Dmine 2015
DW	0.50	0.75	0.80	0.82	0.49	0.70	0.71	0.84
XH	0.83	0.60	0.66	0.86	0.88	0.49	0.65	0.81
AB	0.32	0.56	0.59	0.25	0.26	0.45	0.39	0.35
SZ	0.00	0.22	0.00	0.00	0.00	0.04	0.19	0.00
EL	0.96	0.00	0.87	0.97	1.00	0.46	0.87	1.00

HDT

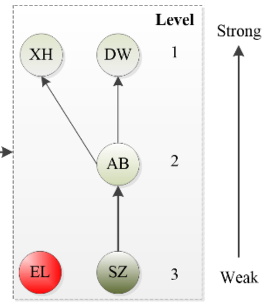


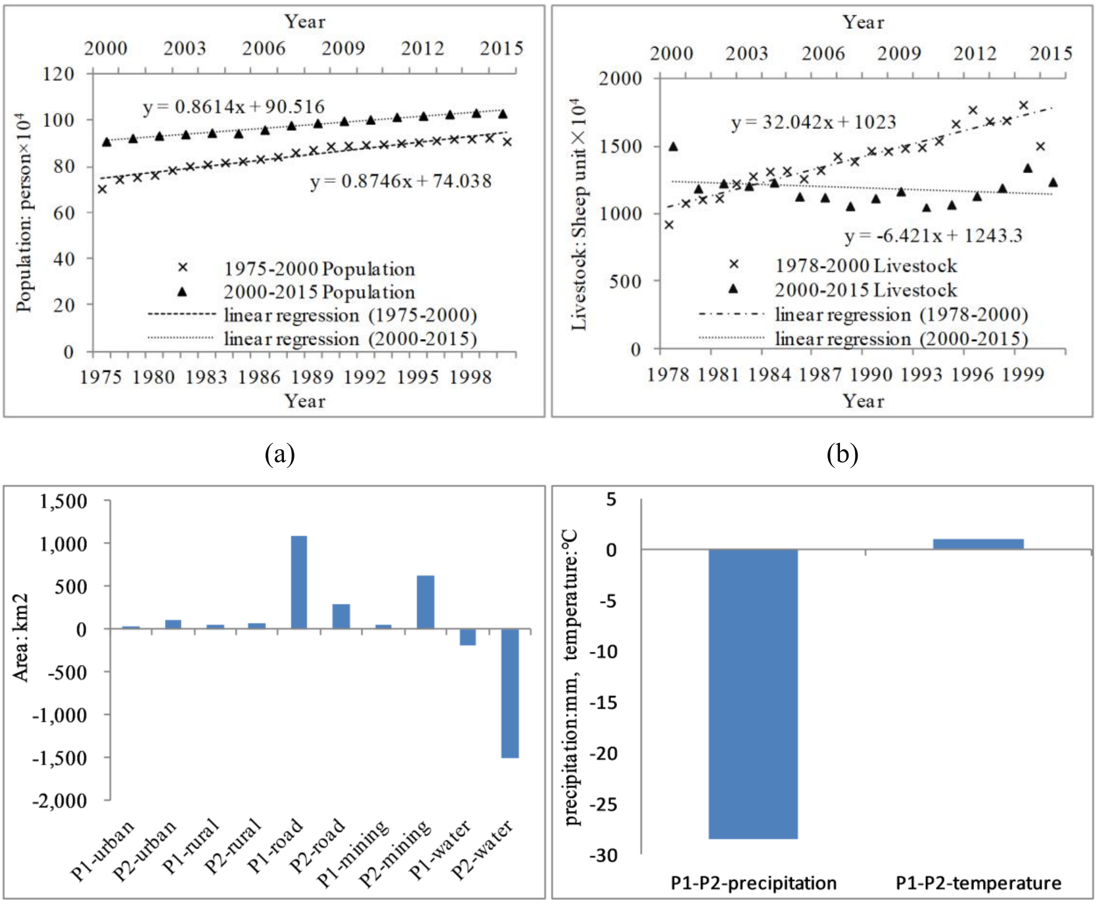
Figure III-3: An example of how HDT was applied for urbanisation between 2000 and 2015 in this study (using input data from Appendix 1-1). Note: XH, DW, AB and SZ are county names. EL as an isolated element can be positioned at any level.

3 Results

3.1 Changes in land degradation drivers in Xilingol

In an attempt to explain the land degradation that has occurred during the past 40 years, we analysed all nine previously selected drivers for the Xilingol area. Linear regression was used to explore the dynamics of population and livestock in both periods (Figure III-4). The total population has increased dramatically since 1975, and the growth rate did not change much over the whole period (Figure III-4a); however, total livestock (in sheep units) increased at an average rate of 32.0×10^4 sheep units per year in the 1975–2000 period, but then decreased at a rate of 6.4×10^4 per year between 2000 and 2015 (see Figure III-4b). Figure III-5e and Figure III-5f show that the median values of livestock density and population density in the LD area initially increased and then decreased in these two periods. Both urban and rural areas have developed in the past four decades, especially in Phase 2 (P2, see Figure III-4c). However, the distance from LD to the nearest urban or rural area (Figure III-5c) initially increased and then decreased over the three dates under investigation (1975, 2000, 2015), respectively. Water bodies, population and livestock experienced a similar trend. The area of water bodies shrunk by 184.7 km^2 and 1,509.0 km^2 over the two periods (see Figure III-4c). Figure III-5g shows that the median value of the distance between an LD area and water bodies initially increased and then decreased at the three points in time. This is mainly due to the disappearance of water bodies after 2000. This transition process is itself a degradation process (Batunacun *et al.*, 2018).

The rate of increase of road and mining areas reached a maximum in both phases. Figure III-5c and Figure III-5d show that the median value of the distance from an LD object to roads and mining decreased at all three points in time, which means the results indicate that over time, LD objects and roads/mines became increasingly closer to each other. When comparing the two periods, the average growth-season temperature also increased (1.0 K), while total annual precipitation decreased (28.4 mm; Figure III-5h and Figure III-5i).



(a) (b)

(c) (d)

Figure III-4: The change in drivers in Xilingol between 1975–2000 and 2000–2015. a) Population, b) Livestock, c) Net area change of urban and rural centres, and roads, mines, surface water bodies, d) Change in precipitation and temperature

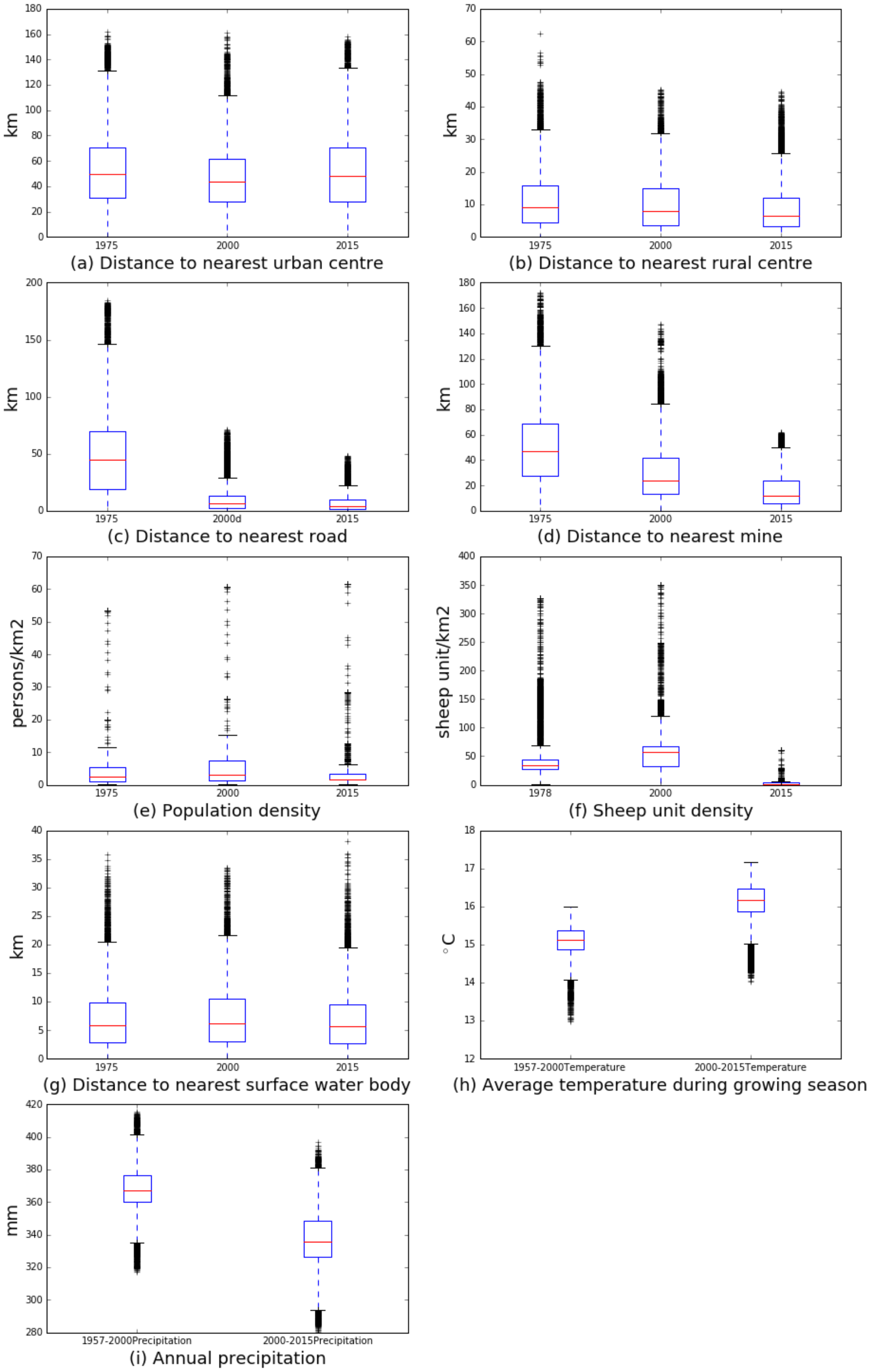


Figure III-5: The state of land degradation drivers at three points in time (temperature and precipitation given as averages between points in time due to their temporal variability)

3.2 Partial order ranking of LD drivers

3.2.1 Partial order ranking of LD drivers during the 1975–2000 period

We analysed the levels, chains, structures and incomparable aspects of counties to identify the order of effect for the three factor groups on LD (Table III-2). Based on the obvious difference in population density and livestock density in all counties, we now focus on two chains with different causalities that were extracted from the data.

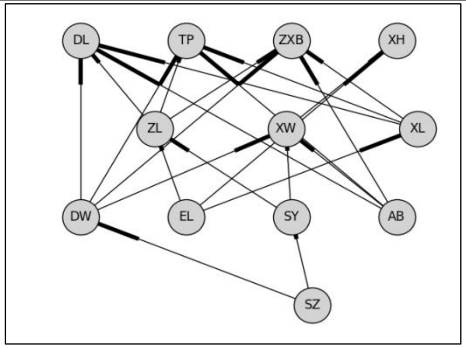
To explore the significant effects from human disturbance more deeply, it was necessary to establish a criterion for the values in this group; when the values fell below 0.1, the effects were ignored. Eleven counties experienced strong effects from livestock density in 1975/78 – 2000 (except for EL, with zero values in both 1978 and 2000, see Table III-2). Based on this, in six grassland counties (XH, DW, XW, SY, SZ and AB), the livestock density was the unique dominant driver. We call the chains that connected these six counties the “dominant livestock” chain ({XH，XW，SY，SZ}, {XH，XW，DW，SZ} and {XH，XW，AB}), where the effect from livestock density decreased along these chains. In contrast, the counties of DL, TP, ZXB, ZL and XL had higher effect values for population and livestock density (see Table III-2a). We called the chains that connected these five counties the “dominant population and livestock” chain ({TP，XL}, {TP，ZL}, {DL，XL}, {DL，ZL}, {ZXB，XL} and {ZXB，ZL}). Both population and livestock density were the dominant drivers for LD in these five counties, and their effect decreased along these chains. EL was a special county, in that it only had high values for human population density. With respect to the spatial distribution of human disturbance drivers, the northern counties (DL, TP, ZXB and XH) suffered significantly from human disturbance; in the agro-pastoral transitional counties (DL and TP) in particular, they were the dominant drivers for LD.

The Hasse diagram for water conditions (Table III-2b) revealed only three levels (the lowest having only one element) and three isolated elements (EL, SY and SZ). This means the Hasse diagram is weakly ordered and, correspondingly, there was no obvious spatial pattern in the impact of water conditions on LD. Climate factors, especially temperature, were the most involved indicators in these three counties (see Table III-1 orientation and Table III-2b).

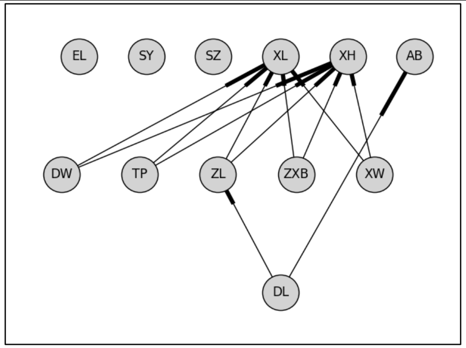
The Hasse diagram for urbanisation (Table III-2c) exhibited four levels and no isolated element, which means we can characterise this Hasse diagram as being strongly ordered. We identified the agro-pastoral counties, TP and DL, as being strongly affected by urbanisation, as they are positioned in the upper levels (TP: Level 1, DL: Level 2, see Table III-2c), while SY and SZ, dominated by sparse grassland and placed in the lowest level, were only nominally affected by urbanisation.

Table III-2: Hasse diagrams and their input data for all indicator groups from 1975 to 2000.
Note: the isolated elements EL, SY, and SZ in Table III-2b could be positioned at any level.

(a) Human disturbance



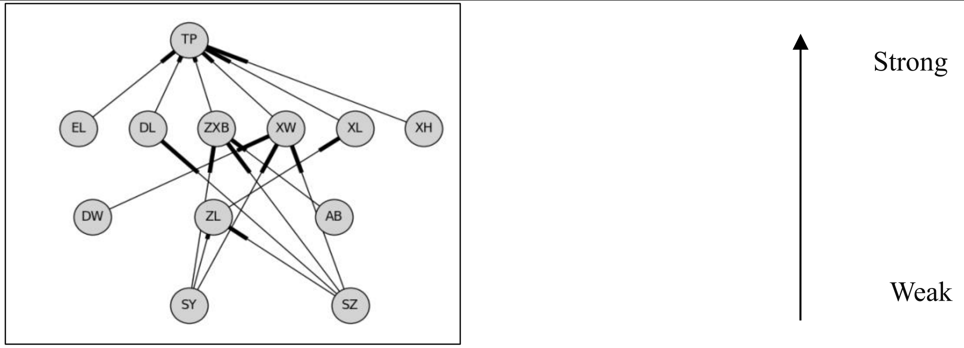
(b) Water conditions



County	Population density 1975	Population density 2000	Sheep unit density 1978	Sheep unit density 2000	Distance to water 2000	Distance to water 1975	Precipitation 1958–2000	Temperature 1958–2000
DW	0.01	0.02	0.12	0.40	0.14	0.28	0.00	0.58
EL	0.02	0.05	0.00	0.00	1.00	1.00	1.00	0.00
DL	0.38	0.44	0.73	0.79	0.10	0.19	0.59	0.33
TP	1.00	1.00	1.00	0.53	0.03	0.01	0.01	0.57
ZL	0.11	0.11	0.73	0.38	0.12	0.22	0.81	0.38
ZXB	0.18	0.18	0.75	0.85	0.11	0.12	0.55	0.52
SY	0.03	0.04	0.12	0.24	0.59	0.64	0.54	0.28
SZ	0.00	0.00	0.12	0.15	0.30	0.39	0.83	0.08
XW	0.04	0.04	0.18	0.87	0.00	0.00	0.17	0.76
XL	0.10	0.14	0.01	0.46	0.44	0.36	0.81	1.00

XH	0.08	0.08	0.42	1.00	0.18	0.49	0.89	0.79
AB	0.01	0.01	0.09	0.44	0.35	0.37	0.73	0.34

(c) Urbanisation/industrialisation



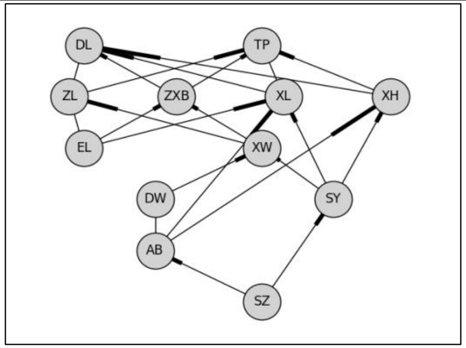
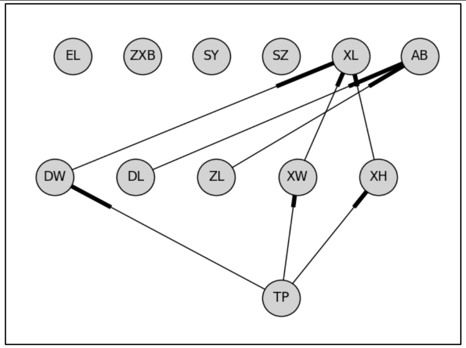
County	Distance to urban land 1975	Distance to settlements 1975	Distance to rural road 1975	Distance to mine 1975	Distance to urban land 2000	Distance to settlements 2000	Distance to rural road 2000	Distance to mine 2000
DW	0.00	0.54	0.29	0.23	0.11	0.60	0.75	0.79
EL	0.77	0.02	0.00	0.79	0.71	0.00	0.62	0.78
DL	0.96	0.61	0.61	0.60	0.94	0.56	0.17	0.43
TP	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ZL	0.49	0.29	0.78	0.70	0.32	0.20	0.40	0.77
ZXB	0.78	0.54	0.69	0.68	0.71	0.49	0.79	0.68
SY	0.47	0.00	0.41	0.28	0.29	0.00	0.14	0.55
SZ	0.25	0.18	0.25	0.09	0.00	0.07	0.00	0.16
XW	0.50	0.67	0.64	0.61	0.34	0.64	0.82	0.85
XL	0.58	0.34	0.91	0.88	0.72	0.34	0.80	0.82

XH	0.87	0.60	0.34	0.00	0.82	0.58	0.77	0.87
AB	0.43	0.45	0.61	0.14	0.36	0.41	0.55	0.00

3.2.2 Partial order ranking of LD drivers during the 2000–2015 period

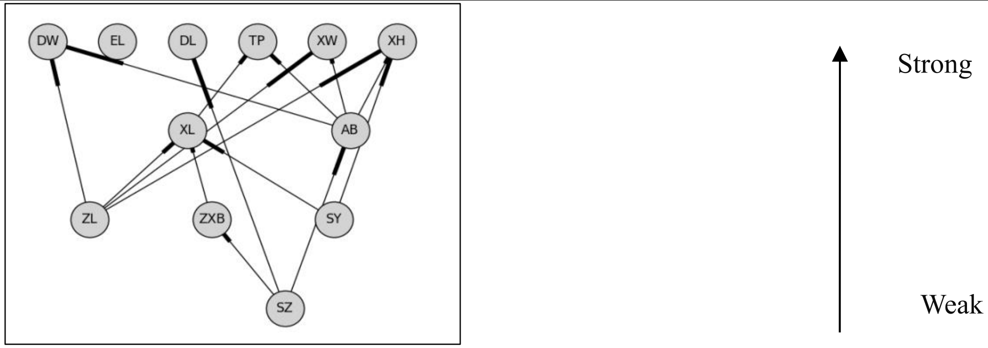
For human disturbance factors, the situation seems to have remained the same during this period. XH, DW, XW, SY, SZ and AB still only suffered from high pressures of livestock density. Table III-3a shows that the chains {XH, AB, SZ}, {XH, SY, SZ}, {XW, DW, AB, SZ} and {XW, SY, SZ} are "high livestock" chains. The chains that connect TP, DL ZL, ZXB and XL ({DL, TP}, {DL, ZXB}, {DL, XL}, {TP, ZL}, {TP, ZXB} and {TP, XL}) are "high population and livestock" chains. EL, with a high value for human population in 2015, suffered more from this driver. Spatially, the southern counties suffered more effects from both population and livestock (both located in the upper level, see Table III-2a). The agro-pastoral counties (DL and TP) were especially affected by human disturbance factors, while the grassland counties (located in lower levels) were dominantly affected by livestock density.
For water conditions during 2000–2015, only three levels emerged, with a small number of chains as well as four isolated elements, indicating that the driver of water conditions is overall weakly ordered. During this period, XL and AB continued to experience significant impact from water conditions, while this driver's effect on XH decreased compared to the earlier period. The agricultural areas (DL, TP) remained largely unaffected (Table III-3b). EL, SY, SZ and ZXB are isolated elements in this period, of which the climate factors in EL, SY and SZ, especially temperature, are mostly responsible for this incomparability (Table III-2b).
Urbanisation drivers increased the number of ordered elements in the uppermost level from one (in the earlier period) to five, indicating an obvious impact of urbanisation across Xilingol after 2000 (Table III-3c). Dense grassland areas (DW, XW, XL, XH) suffered much more from urbanisation, followed by the moderately dense and sparse grassland areas in the northern part of the league (ZL, SY, SZ). The agro-pastoral areas DL and TP were also among those counties that suffered greatly from urbanisation in this period. EL is an isolated element, with a zero value for indicator Drural_2000 (Table III-2c).

Table III-3: Hasse diagrams and their input data for all indicator groups from 2000 to 2015
Note: the isolated elements EL, ZXB, SY and SZ in Table III-2b could be positioned at any level, as well as EL in Table III-2c.

(a) 2000–2015 Human disturbance					(b) 2000–2015 Water conditions			
								
County	Population density 2000	Population density 2015	Sheep unit density 2000	Sheep density 2015	Distance to water 2000	Distance to water 2015	Precipitation 2000–2015	Temperature 2000–2015
DW	0.01	0.02	0.29	0.48	0.42	0.28	0.29	0.80
EL	0.05	0.11	0.00	0.00	1.00	1.00	0.85	0.22
DL	0.44	0.47	0.82	1.00	0.49	0.41	0.37	0.35
TP	1.00	1.00	1.00	0.99	0.00	0.00	0.00	0.49
ZL	0.12	0.12	0.48	0.77	0.60	0.25	0.58	0.42
ZXB	0.18	0.18	0.36	0.81	0.56	0.26	0.52	0.48
SY	0.04	0.04	0.17	0.28	0.98	0.99	0.49	0.31
SZ	0.00	0.00	0.11	0.25	0.64	0.62	1.00	0.00
XW	0.05	0.06	0.33	0.73	0.21	0.26	0.51	0.75
XL	0.14	0.20	0.30	0.39	0.48	0.45	0.70	1.00
XH	0.08	0.09	0.28	0.84	0.40	0.31	0.56	0.54

AB	0.01	0.01	0.26	0.39	0.64	0.66	0.72	0.42

(c) 2000-2015 Urbanisation/industrialisation



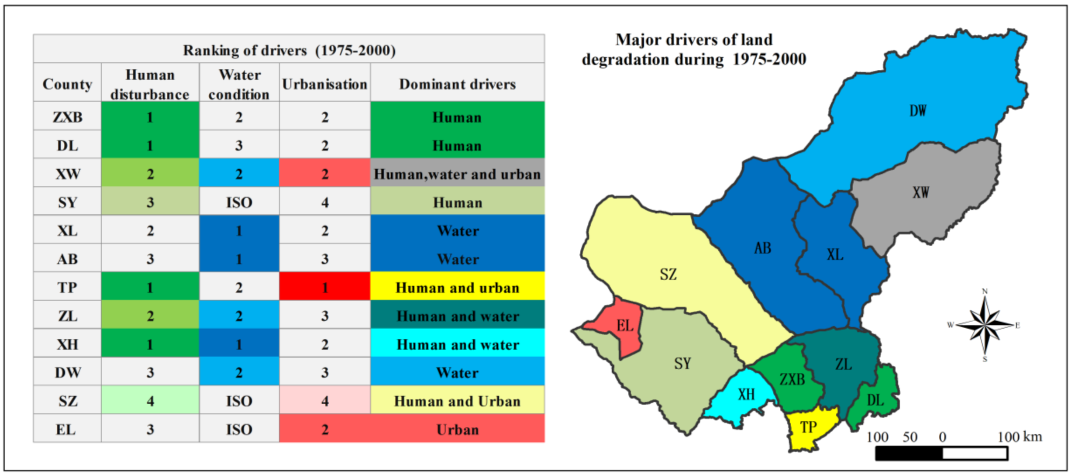
County	Distance to urban land 2000	Distance to rural settlements 2000	Distance to road 2000	Distance to mine 2000	Distance to urban land 2015	Distance to rural settlements 2015	Distance to road 2015	Distance to mine 2015
DW	0.50	0.75	0.80	0.82	0.49	0.70	0.71	0.84
EL	0.96	0.00	0.87	0.97	1.00	0.46	0.87	1.00
DL	0.96	0.85	0.48	0.62	0.88	0.82	0.78	0.93
TP	1.00	1.00	1.00	1.00	0.92	1.00	1.00	0.79
ZL	0.44	0.19	0.38	0.72	0.38	0.00	0.32	0.49
ZXB	0.62	0.31	0.69	0.60	0.69	0.16	0.50	0.44
SY	0.58	0.27	0.30	0.71	0.53	0.12	0.00	0.49
SZ	0.00	0.22	0.00	0.00	0.00	0.04	0.19	0.00
XW	0.50	0.69	0.88	0.93	0.53	0.66	0.85	0.88
XL	0.82	0.54	0.88	0.86	0.78	0.47	0.83	0.79
XH	0.83	0.60	0.66	0.86	0.88	0.49	0.65	0.81
AB	0.32	0.56	0.59	0.25	0.26	0.45	0.39	0.35

3.2.3 Order rankings for all drivers of land degradation in the two periods

In this section, we transformed all comparison results into ranks for all drivers for the two periods; Section 2.4.3 above laid out an explanation for the orientation of the levels. Driver groups that were found to be dominant were positioned at the top of the diagram. The identification of levels and isolated elements from the Hasse diagrams can help us to understand the major drivers of LD at the county level. During the 1975–2000 period, human disturbance was the dominant driver group in eight counties (ZXB, DL, XW, SY, TP, ZL, XH and SZ; see Figure III-6a). Human disturbance had the strongest effect in ZXB, DL, TP and XH, followed by XW, ZL, SY and DW. Water conditions constituted a dominant driver group in five counties, where XL, AB and XH were affected most by water conditions, followed by XW, ZL and DW. Urbanisation was a dominant driver group in TP, followed by XW, EL and SZ. Ultimately, human disturbance was the only dominant driver group in ZXB, DL and SY; water conditions served as the major driver group in XL, AB and DW; both human disturbance and urbanisation were major driver groups in TP and SZ; and human disturbance and water conditions were the dominant driver groups in ZL and XH. In XW, all three groups affected LD similarly (Figure III-6a).

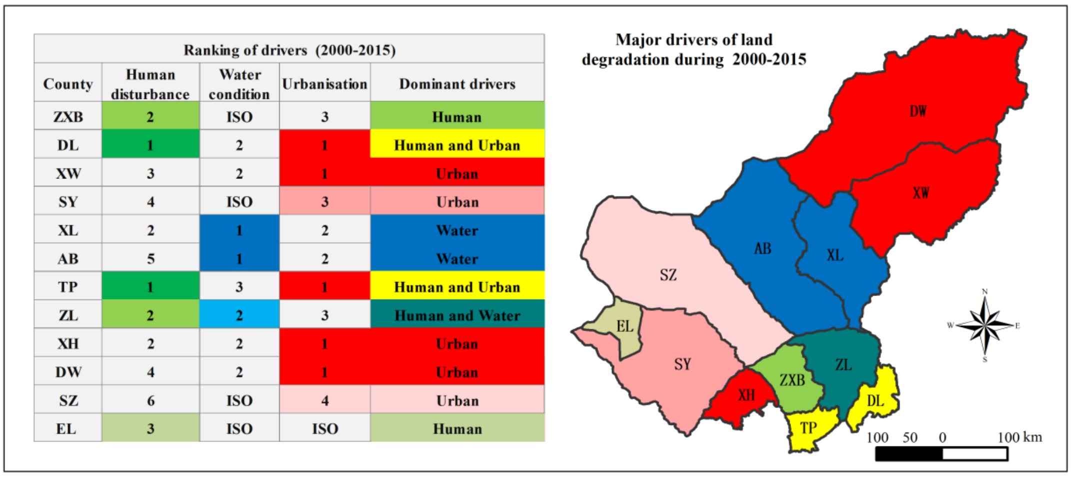
After 2000, the dominant drivers changed significantly in all counties. Human disturbance was now the major driver group in five counties (ZXB, DL, TP, ZL, EL), of which DL and TP suffered the most significant effects (Figure III-6b). Water conditions emerged as the major driver group in three counties: XL, AB and ZL. Urbanisation was the dominant driver group in seven counties, of which DL, XW, TP, XH and DW were influenced most heavily, followed by SY and SZ. Above all, human disturbance was the major driver group in ZXB and EL; the water conditions group was the dominant driver group in XL and AB. Human disturbance and urbanisation were the major driver groups in DL and TP; urbanisation was the dominant driver group in XW, XH and DW; and water conditions and urbanisation were the major driver groups in XL and AB (see Figure III-6b).

After ranking all the drivers, we compared the ranking results for both periods. The major driver groups in TP, XL, AB and ZL remained unchanged. Otherwise, as a more general observation, the effect from urbanisation increased, and has now become more dominant than human disturbance, and water conditions effects decreased after 2000. In the agro-pastoral areas, effects from human disturbance and urbanisation either remained steady (TP) or increased (DL) after 2000.



Ranking of drivers (1975-2000)				
County	Human disturbance	Water condition	Urbanisation	Dominant drivers
ZXB	1	2	2	Human
DL	1	3	2	Human
XW	2	2	2	Human,water and urban
SY	3	ISO	4	Human
XL	2	1	2	Water
AB	3	1	3	Water
TP	1	2	1	Human and urban
ZL	2	2	3	Human and water
XH	1	1	2	Human and water
DW	3	2	3	Water
SZ	4	ISO	4	Human and Urban
EL	3	ISO	2	Urban

(a)



Ranking of drivers (2000-2015)				
County	Human disturbance	Water condition	Urbanisation	Dominant drivers
ZXB	2	ISO	3	Human
DL	1	2	1	Human and Urban
XW	3	2	1	Urban
SY	4	ISO	3	Urban
XL	2	1	2	Water
AB	5	1	2	Water
TP	1	3	1	Human and Urban
ZL	2	2	3	Human and Water
XH	2	2	1	Urban
DW	4	2	1	Urban
SZ	6	ISO	4	Urban
EL	3	ISO	ISO	Human

(b)

Figure III-6: The major drivers and their ranking in each county between two periods (a: 1975–2000, b: 2000–2015). Note: The colour represents the identified type of most dominant drivers. ISO refers to an isolated element, indicating no dominant driver for the respective category in this county.

4 Discussion

Partial ordering resulted in a ranking of all drivers that had the greatest impact on LD in Xilingol. The identification of these levels, as well as the combination of maximal, minimal and isolated elements, facilitates scientific understanding of the major drivers of LD in this region. Since national policies have an important effect on stakeholders' decisions and land management practices, it is necessary to analyse the relationships between these drivers and policies under the current situation. Figure III-7 depicts a summary of the vast literature relating to policy, human disturbance, urbanisation and water conditions for the period from 1978 to 2050. The graphic only covers the topics and causal relationships at the focus of this paper.

4.1 Policy structures in Xilingol since 1978

A total of eight national and/or regional policies have been carried out in this region since 1978. We have grouped all policies into three categories according to their aims and real-world effects (see Table III-4 for abbreviations): (1) Economic Stimulus policies (ES): ER, HPRS; (2) policies that Control Human Pressure (CHP): RGG, FGMU and PES, aiming to reduce livestock and users on grassland; and (3) polices that Combat LD (CLD): GFGP, BTSSCE and TNSFS, which have attempted to improve environmental conditions (e.g. by afforestation; Table III-4). Before 2000, the Household Production Responsibility System (HPRS) was enacted, radically changing the system of property rights. The objective of the HPRS was to assign livestock and grassland to the herder's household; the goals were to both stimulate economic development and to protect the environment in Xilingol. However, the HPRS has been shown to have led to rather short-term economic development and to further degradation of grassland (Li & Huntsinger, 2011). Since 2000, six national environmental protection policies have been implemented in Xilingol. Their aims and time scale are summarised in Table III-4.

Table III-4: Description of major national policies in Xilingol.

Periods	Policy Groups	Policy Name	Time Period	Measures	Aims
Pre-2000	ES	The reform and opening-up policy (henceforth: Economic Reform, ER)	1978 to present	(1) Economic reform (2) Economic and societal opening	Accelerate economic development
		Household Production Responsibility System (HPRS)(Akram *et al.*, 2009)	1980s to 1990s	Assignment of grassland property to an individual household	(1) Control overgrazing (2) Help rangeland restoration (3) Improve livestock production
	CHP	Fencing Grassland and Moving Users (FGMU) (Akram *et al.*, 2009; Bijoor *et al.*, 2006)	2002 –2008	(1) Grazing restrictions (grazing ban or rotational grazing) (2) The transfer of inhabitants (3) Promotion of high-yield agriculture (4) Imports of high-value livestock	Restore heavily degraded grassland
		Returning Grazing to Grassland (RGG) (Liu, 2017; Rahimi, 2016)	2000–2020	(1) Grazing ban (2) Rotational grazing (3) The setting of a deterministic stocking rate	(1) Restrict grazing (2) Conserve heavily degraded grassland by sowing grass
		Payments for Environmental Services (PES) (Démurger & Pelletier, 2015; Meyer *et al.*, 2015; Uthes *et al.*, 2010a)	2010–2020	(1) Grazing prohibition subsidies (2) Grass grazing balance subsidies (3) Grass seed subsidies (4) Performance appraisal awards	Achieve a win-win situation in terms of both environmental protection and poverty alleviation
	CLD	Beijing-Tianjin Sand Source Control Engineering Project (BTSSCE) (Zeng *et al.*, 2014)	2001 to present	(1) Afforestation (2) Sandy land restoration	Reduce wind-induced soil loss and related sandstorms in the Beijing-Tianjin megacity belt
		"Three Norths" Shelter Forest System (TNSFS) (Cao, 2008)	1987–2050	Afforestation	Mitigate desertification
		Grain for Green Programme (GFGP) (Liu *et al.*, 2014)	2001–2010	(1) The restoration of cropland to forest or grassland	Convert croplands on steep slopes to forest or

		(2) The conversion of barren land to forest on steep slopes by providing farmers with food and cash subsidies	grassland

4.2 The relationship between drivers of land use changes and political policies

4.2.1 Drivers related to economic reform policies up to 2000

During the 1975–2000 period, human disturbance was the dominant driver in eight counties (ZXB, DL, TP, XH, XW, ZL, SY and SZ). The economic reform in 1978 and the HPRS in the 1980s led to significant increases in population and livestock density (Jiang *et al.*, 2006), which was shown to be the major cause of degradation in this area. Economic reform encouraged husbandry development, which is why a considerable number of Han people migrated to the grassland areas of Xilingol in this period (Jiang *et al.*, 2006). Due to this policy intervention, long-term overgrazing became the direct cause of grassland degradation, behind which we find demand for livestock products on the part of the increasing population to be the ultimate driving force (Kawamura *et al.*, 2005; Zheng *et al.*, 2011).

4.2.2 Drivers related to ecological protection policies after 2000

After 2000, ecological protection polices had a considerable impact on the local environment. Some of the identified links between polices, human disturbance (population and livestock) and land degradation developed in a similar pattern. For one thing, ecological policies had a direct impact on human disturbance factors. Many previous studies have suggested that the CHP policies have worked effectively in part of Xilingol (Du *et al.*, 2016; Li & Huntsinger, 2011; Waldron *et al.*, 2010), and the partial order results in our study indeed show that the effects caused by human disturbance have largely decreased. At the same time, livestock numbers have also decreased (Figure III-4b). The four counties in which human disturbance continuously causes LD (DL, ZL, TP and ZXB) are located in the south of Xilingol (ZXB, DL, TP, ZL, EL, see Figure III-6b), where population figures are high and grassland resources are limited (Sun *et al.*, 2017; Wuyinga & Haishan, 2017). These circumstances have resulted in poverty, reinforcing negative trends. More livestock was kept in the hope of generating income, which led to further degradation and further poverty – a vicious cycle of poverty and LD. Consequently, in these areas, reducing population pressures would be the radical answer. Recommendations have included support for continuing to carry out anti-poverty policies, encouraging stockbreeding diversity and developing more livestock-related industry to alleviate poverty and degradation (Wuyinga & Haishan, 2017; Zheng *et al.*, 2011).

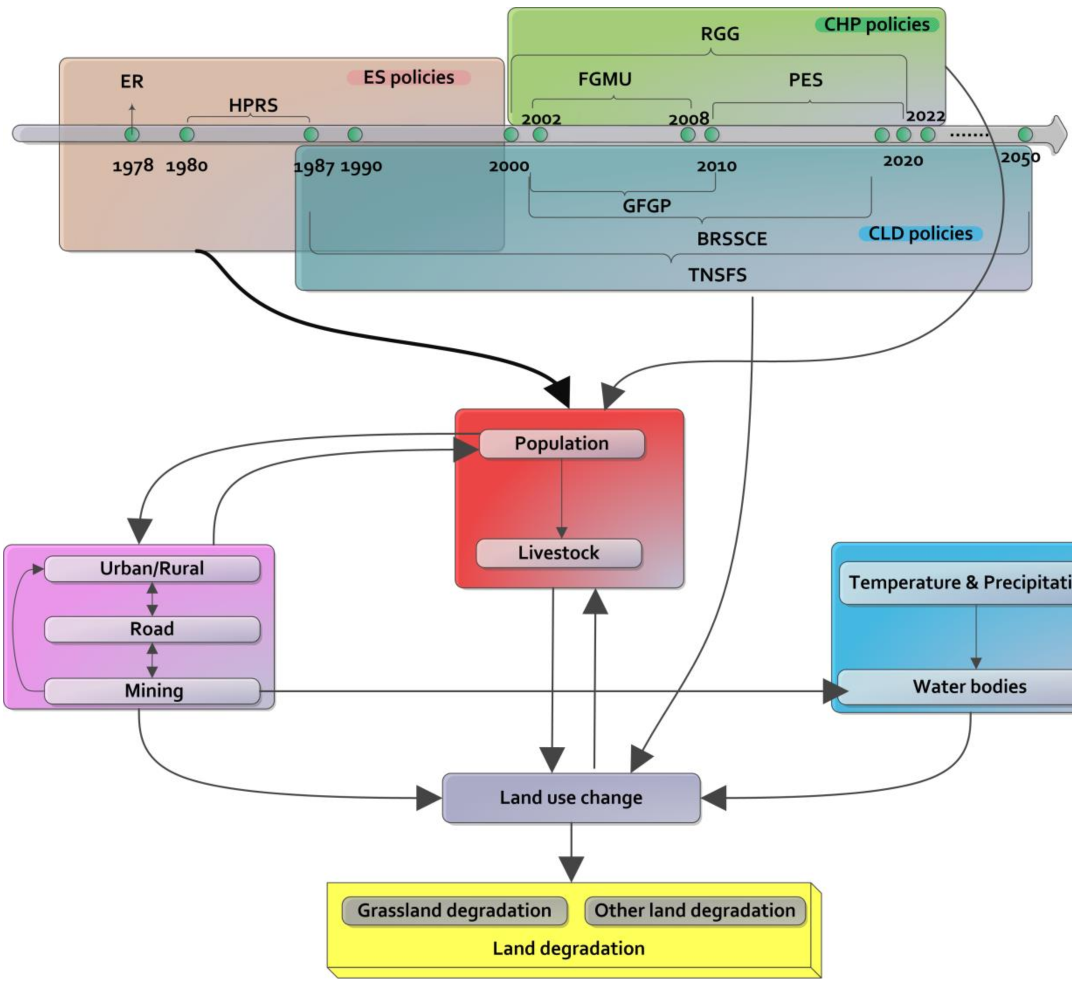


Figure III-7: Schematic concept of the interplay between policy, land degradation and related drivers. Note: The green dots represent the point in time at which policies were implemented.

The identified link between human disturbance, urbanisation and LD after 2000 is obvious. The increasing population accelerated urban and rural expansion and road development. In addition, the development of coal mining and related heavy industry, such as coal-based power generation and petrochemical processing, also accelerated as a consequence of road construction and the increase in urban areas with cheap labour. After 2000, all the policies that were meant to stimulate the economy targeted livestock restrictions (in the form of grazing bans or maximum stock rates) and the relocation of herders (partly into cities), which subsequently drove urban land expansion. Development in urban as well as rural areas and the accompanying road construction mainly took place in high-quality grassland areas and led to grassland fragmentation, seriously threatening the region's biodiversity. Regulations like the "Xilingol Urban Development Plan" (also known as the Xilingol master plan) were set up to alleviate this problem, but there still is a lack of policies or regulations that effectively protect the areas surrounding urban/rural land. Our findings show that after 2000, the average distance from both urban and rural population centres to LD has increased (see Figure III-5a and b), which means that the ecological protection measures have worked effectively in this respect. However, since unwanted side effects have occurred, related measures such as grazing bans or fencing requirements

must now be taken to protect the remaining grassland areas close to emerging cities or rural population centres.
Mining has emerged as the top source of income in Xilingol. After a set of restrictions related to stockbreeding (e.g. grazing bans and rotation grazing, see Table III-2) had been enacted, mining became the major industry in 2008, which it has been ever since (Yang et al., 2014). Coal mining from surface mines consumes considerable land area, while the subsequent petrochemical processes require large quantities of water. Mining also causes the most dramatic and rapid land use changes, affecting soil, groundwater aquifers, and surface waters, due to the removal of topsoil, the enormous use of water, and the deposition of huge amounts of excavation material on the surface (Qian *et al.*, 2014). Our results demonstrate that after 2000, urbanisation and industrialisation – i.e. mining – has become the dominant type of driver of LD in Xilingol in seven counties (DL, XW, SY, TP, XH, XW and SZ). Yang et al. (2011) reported that rapid urbanisation and industrialisation had altered the ecological footprint dramatically.
Water availability in the Xilingol region is an important biophysical factor that determines the natural productivity of grasslands, but that also ensures the quality of life for the people themselves. The causality between mining, water conditions and land degradation is also significant. Our findings show that water bodies have shrunk considerably, while the climate has become warmer and drier. Increased water consumption through mining, higher evapotranspiration at warmer temperatures, and less rainfall have consequently all lead to the reduced availability of water resources, demonstrated by lower groundwater tables and decreased surface areas of lakes and lower levels of river discharge. In fact, groundwater levels in Inner Mongolia have been falling for decades, even though this development is not seen as being outside natural fluctuations at this stage (Brutsaert & Sugita, 2008; Davi *et al.*, 2013). Statements concerning water availability are greatly impaired by the very limited number of stations that monitor long-term groundwater levels on the Mongolian plateau. Tao et al. (2015) suggested that surface water shrinkage in grassland areas is mainly caused by the development of coal mining. Moreover, Qian et al. (2014) showed that coal mining, coal-based power generation and petrochemical processing had all been using extremely high quantities of water. To meet the water demands of coal-based industries, local rivers and their tributaries have been dammed, and many wells have been dug (Tao *et al.*, 2015b). At the same time, the climate itself has had a negative effect on the size of surface water bodies. There have been attempts to actively restore the ecological value ofdesertified land by replanting. However, geologists assume that parts of the areas lost to desertification will remain that way forever (Yang *et al.*, 2015).

4.3 Application of partial order theory

It is crucial to compare the different factors of LD to evaluate and adjust current ecological policies, and provide information for future decision-making processes. Since the factors of LD are complex and cannot be reduced to single components, earlier studies applied different multi-criteria decision methods, such as the Analytic Hierarchy Process, Cluster Analysis, Logistic Regression or the HDT

(Kardaetz *et al.*, 2008; Lin *et al.*, 2014; Memarbashi *et al.*, 2017; Müller-Hansen *et al.*, 2017). Principle Component Analysis (PCA) is also well-suited to identifying the first and second major drivers (components) for land use change based on available driver data (Yan-fen *et al.*, 2008). However, PCA is a linear approach, and for this reason it is not suitable for detecting the non-linear relationship between drivers and effects between different counties. In contrast, HDT is able to extract information from comparable elements, as well as extracting information from incomparable elements as well. For example, Figure III-2 indicates that XH and DW are incomparable elements; while both counties suffered from urbanisation pressures, the means were different (XH was more affected by urban area expansion, while DW responded more to road and mining development). Moreover, the method allows for a "data-driven" analysis on the one side, and a combination with expert knowledge on the other, e.g. during the orientation process or the identification of chains or isolated elements.

In addition, analysis of the Hasse diagram structure, its priority elements and its pattern of indicators together revealed the major drivers of LD over territory and time. In this research, we collected nine drivers and grouped them into three categories, comparing and ranking these major drivers at the county level. This process enabled us to derive recommendations according to the dominant drivers in each county. These results can provide important information to develop scenarios of different land use models (e.g. CLUE-S, LandSHIFT, alucR) which address the regional variation in dominant drivers in the study area.

Moreover, analysis of HDT is relatively flexible, and not only depends on the goals, but also the tolerance of stakeholders. For example, in Figure III-3, EL is an isolated element within the urbanisation drivers group, with the smallest value of Drural_2000 and the largest values of Durban_2000, Droad_2000, Dmine_2000, Durban_2015, Droad_2015, Dmine_2015 (see Figure III-3). If we reset the tolerance of the effects from this driver group, we could remove rural drivers in 2000 and even in 2015. As a consequence, EL would become the uppermost element and urbanisation would turn out to be the dominant driver for LD in EL.

However, in the present study, all effects from all drivers have been fully considered and no driver was ignored. In addition, in this study, we have selected a non-robust statistical method to process the data (normalisation, see Equation 4). Alternatively, a standard scalar or a binary scalar could also be used to explore the data. Furthermore, due to limitations on the acquisition of rural population data (the earliest statistical records for rural population in this region date back to 1995), this study was unable to distinguish between rural and urban population. For this reason, we used total population as an indicator, but if better data were available, this indicator could be revisited.

5 Conclusions and suggestions for future policy development

In this study, we identified the drivers of land degradation and their dynamics in Xilingol, and analysed the variation of the dominant groups of drivers over territory and time at the county level. We found that population figures and urban, rural, road and mining areas increased between 1975 and 2015, while numbers of livestock initially increased and then decreased before and after 2000. Water bodies have decreased over the past four decades, and the climate has become warmer and drier in this region, with increasing temperature and decreasing precipitation. These results indicate that the effects of direct human disturbance on LD have declined, and the coincidence of this decline with the implementation of major ecological policies suggests that these policies have indeed been the major cause of this decrease (we showed that the average distance from urban/rural centres to LD increased after 2000). However, at the same time, the expansion of rural and urban centres, road construction and mining have further increased, and in the investigated period after 2000, these factors developed into the predominant drivers for LD, especially in non-agricultural areas, even outperforming the effects of decreasing water resources (though these still remain an important driver). In agro-pastoral areas (TP and DL), human disturbance was dominantly responsible for LD in both periods.

While previous ecological reform and conservation policies have been an obvious success with respect to the target for which they were developed, unwanted side effects have nevertheless occurred. Much of the urbanisation and industrialisation that has been observed after 2000 can also be attributed to these policies. As these emerging factors continue to drive LD along different pathways, it is now necessary to continue working on measures that protect the remaining grassland areas close to emerging cities or rural centres, such as the implementation of grazing bans or fencing. Keeping this political pressure high is essential for the protection of the ecological resources and the cultural heritage of Xilingol and the Mongolian Plateau, but it can only lead to the desired outcome if it is accompanied by additional measures that use different levers. In counties where the direct effects of human disturbance and urbanisation dominate, policy may need to address poverty, such as through increasing stockbreeding diversity and the development of more livestock-related and tourism-related businesses. In counties in which LD continues to be driven by high livestock numbers, livestock control needs to be continuously enforced, e.g. through policy measures such as grazing bans, imports of high-value livestock, deterministic stocking rates and grazing prohibition subsidies that have already been launched in Xilingol.

For the development of more sustainable land use in Xilingol with a focus on grassland ecosystem protection, two further targets for political action are clearly identifiable:

Against the background of diminishing water resources, the government should focus on developing clean energy concepts, and improve coalmining technologies to reduce water consumption and conserve the precious groundwater resources that the local society so critically relies on. When the use of water for energy supply and mining conflicts, policy has to work towards improved water use efficiency of industrial processes, support for green procurement in the energy sector and the integration of water resources as an equally important target in decisions on energy and mining development. This is particularly challenging, as water resource management requires multinational planning and policy implementations at the catchment or groundwater basin level.

It has also become evident that the mining industry needs to be targeted more directly in future policy developments. This may include increased political pressure to improve the efficiency of coal mining in general (not only with respect to water use), which may lead to providing constant coal production with a reduced number of active mines. More rigid mining planning, e.g. regulating the number of mining licences and thereby reducing the overall number of mines that are operating at the same time, may prove helpful. Policy development could also work to increase awareness about the ecological reclamation of completely exhausted mines, especially in the counties that currently exhibit the most active coalmining industry – AB, DW, XW and XL – and provide the required political pressure to enforce such restoration (Sun *et al.*, 2017). In the end, more intensive migration and settlement control seems necessary to organise labour availability for the mines and to organise urban and rural expansion more effectively. This should be organised with respect to the county-specific characteristics that exist among the distinct areas of Xilingol as a result of varying drivers, which we have been able to show by means of POR.

In sum, we have demonstrated that drivers for LD in the Xilingol area have exhibited distinct temporal dynamics over the last 40 years, with a spatial pattern showing that different drivers dominate different areas in the League. This calls for county-tailored policy measures to combat further grassland degradation and to sustain the ecological value and cultural heritage of Xilingol, while maintaining sufficiently high income levels and standards of living.

Acknowledgements

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Supplementary Information

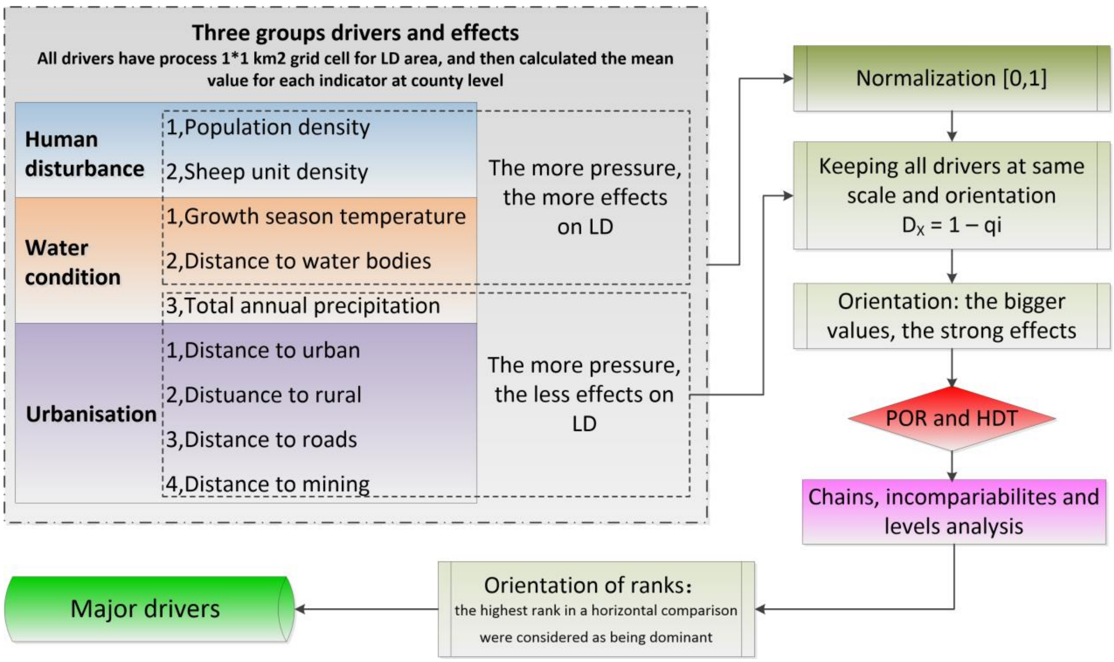

Figure SI III-1: The structure of identifying dominant driver for LD

Chapter IV:

Using SHAP to interpret XGBoost predictions of grassland degradation in Xilingol, China.

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Abstract

Machine learning (ML) and data-driven approaches are increasingly used in many research areas. XGBoost is a tree boosting method that has evolved into a state-of-the-art approach for many ML challenges. However, it has rarely been used in simulations of land use change so far. Xilingol, a typical region for research on serious grassland degradation and its drivers, was selected as a case study to test whether XGBoost can provide alternative insights that conventional land-use models are unable to generate. A set of twenty drivers was analysed using XGBoost, involving four alternative sampling strategies, and SHAP to interpret the results of the purely data-driven approach. The results indicated that, with three of the sampling strategies (over-balanced, balanced and imbalanced), XGBoost achieved similar and robust simulation results. SHAP values were useful for analysing the complex relationship between the different drivers of grassland degradation. Four drivers accounted for 99% of the grassland degradation dynamics in Xilingol. These four drivers were spatially allocated, and a risk map of further degradation was produced. The limitations of using XGBoost to predict future land-use change are discussed.

Key words: grassland degradation, machine learning, driver-driven method, XGBoost, SHAP values

1 Introduction

Land-use and land-cover change (LUCC) has received increasing attention in recent years (Aburas et al., 2019; Diouf & Lambin, 2001; Lambin et al., 2003; Verburg et al., 2002). Land-use change includes various land-use processes, such as urbanisation, land degradation, water body shrinkage, and surface mining, and has significant effects on ecosystem services and functions (Sohl & Benjamin, 2012). Grassland is the major land-use type on the Mongolian Plateau; its degradation was first witnessed in the 1960s. About 15% of the total grassland area was characterised as being degraded in the 1970s, which rose to 50% in the mid-1980s (Kwon *et al.*, 2016). In general, grassland degradation (GD) refers to any biotic disturbance in which grass struggles to grow or can no longer exist due to physical stress (e.g. overgrazing, trampling) or changes in growing conditions (e.g. climate; Akiyama & Kawamura, 2007). In this study, grassland degradation is defined as grassland that has been destroyed and subsequently classified as some other land use, or that has significantly decreased in coverage.

Grassland is a land use that provides extensive ecosystem services (Bengtsson *et al.*, 2019). When degraded, the consequences are seen in an immediate decline in these services, such as a decrease in carbon storage due to a reduction in vegetation productivity (Li *et al.*, 2017c). About 90% of carbon in grassland ecosystems is stored in the soil (Nkonya *et al.*, 2016). Furthermore, GD results in a reduction in plant diversity and above-ground biomass available for grazing (Wang *et al.*, 2014). Likewise, GD leads to soil erosion and frequent dusts storms in Inner Mongolia (Hoffmann *et al.*, 2008; Reiche, 2014). Drivers of GD are manifold, and have been analysed in a range of studies (Li *et al.*, 2012b; Liu *et al.*, 2019a; Sun *et al.*, 2017; Xie & Sha, 2012). However, few studies use sophisticated driver analysis to predict spatial patterns of GD (Jacquin *et al.*, 2016; Wang *et al.*, 2018b). A number of studies have addressed the complex relationship between GD and its drivers (Cao *et al.*, 2013; Feng *et al.*, 2011; Fu *et al.*, 2018; Tiscornia *et al.*, 2019). However, these studies focus mainly on visualising or describing non-linear relationships between GD and its drivers.

The aim of developing various land-use models was to explore the causes and outcomes of land-use dynamics; these models were implemented in combination with scenario analysis to support land management and decision-making (National Research Council, 2014; Ren *et al.*, 2019). Most such models are statistical models, such as logistic regression models or models based on principle component analysis (Li *et al.*, 2013; Lin *et al.*, 2014) or Bayesian belief networks (Krüger & Lakes, 2015). Some such models are spatial (e.g. CLUE-S, GeoSOS-FLUS, LTM, Fu *et al.*, 2018; Liang *et al.*, 2018; Pijanowski *et al.*, 2002, 2005; Verburg & Veldkamp, 2004; Zhang *et al.*, 2013); others are not (e.g. Markov models; Iacono et al., 2015; Yuan et al., 2015). Hybrid models, which combine different approaches to make the best use of the advantages of each model, are another important variety. This type of model is used to characterise the multiple aspects of LUCC patterns and processes (Li & Yeh, 2002; Sun & Müller, 2013). In most cases of land-use change, it was either assumed that the relationship between the drivers and the resulting land-use change is constant over time (Fu *et al.*, 2018; Samie *et al.*, 2017; Zhan J Y *et al.*, 2007), or the relationships were identified as being linear or non-linear, but were not interpreted (Tayyebi & Pijanowski, 2014). We hypothesise that the relationships between GD and its drivers are mainly non-linear. We therefore see a need for methods that are capable of analysing and interpreting non-linear relationships between GD and dynamic drivers.

With the development of computer science, machine learning (ML) models have been increasingly used in land-use change modelling (Islam *et al.*, 2018; Krüger & Lakes, 2015; Lakes *et al.*, 2009; Tayyebi & Pijanowski, 2014). ML is superior to the human brain when it comes to pattern recognition in large datasets, e.g. images and sensor fields. Once the task is defined and the data for training is provided, ML operates without any further human assistance. Various ML approaches have been used in the analysis of land-use change processes, the most prominent of which being Support Vector Machines (SVM, Huang *et al.*, 2009, 2010), Artificial Neural Networks (ANN, Ahmadlou *et al.*, 2016; Yang *et al.*, 2016), Classification And Regression Trees (Tayyebi & Pijanowski, 2014) and Random Forest (RF, Freeman *et al.*, 2016). While the different ML approaches generally perform well in identifying patterns, they remain a black box and make no contribution to our understanding of how the underlying drivers act on the LUCC process. Compared to linear methods such as logistic regression, ML models often achieve higher accuracy and capture non-linear land-use change processes. Likewise, ML models relax some of the rigorous assumptions inherent in conventional models, but at the expense of an unknown contribution of parameters to the outcomes (Lakes *et al.*, 2009). However, the key challenge is to crack the black box and reveal how each driver affects the land-use change pattern or processes in the ML models.

The eXtreme Gradient Boosting (XGBoost) method has recently been developed as a supervised machine learning approach (Chen & Guestrin, 2016). XGBoost algorithms have achieved superior results in many ML challenges; they are characterised by being ten times faster than popular existing solutions, and the ability to handle sparse datasets and to process hundreds of millions of examples. XGBoost has already been used in land-use change detection, combined with remote sensing data (Georganos *et al.*, 2018), but has not yet been used in the simulation and prediction of land-use change. SHapley Additive exPlanations (SHAP; Lundberg & Lee, 2016) is a unified approach to explain the output of any ML model and to visualise and describe the complex causal relationship between driving forces and the prediction target. We propose using SHAP to analyse the driver relationships hidden in the black box model of XGBoost when employed for land-use change modelling.

Having earlier used a clustering approach to identify drivers of GD in a case study in Inner Mongolia (Xilingol League; Batunacun *et al.*, 2019), we now use XGBoost and SHAP to simulate GD dynamics across the same area. We are primarily interested in learning whether ML models can achieve a better predictive quality than linear methods, in addition to improving our understanding of how grassland degrades in Xilingol. In the intention to identify areas with a high risk of further degradation and to determine the drivers responsible for progressive degradation, we used XGBoost to generate a data-driven model to explore the GD patterns. We then used SHAP to open the non-linear relationships of the black box model stepwise, and transformed these relationships into interpretable rules. The resulting model enabled us to map the primary GD drivers and GD hot spots in Xilingol.

2 Materials and methods

2.1 Study area

The Xilingol League is located about 600 km north of Beijing (He *et al.*, 2004), in the centre of Inner Mongolia. This administrative unit, covering an area of 206,000 km^2, spans from 41.4°N to 46.6°N and from 111.1°E to 119.7°E (Figure IV-1). The area is dominated by the continental temperate semiarid climate. The frequent droughts (in summer) and “dzud” (an extremely harsh and snow-rich winter) are the major natural disasters that occasionally lead to catastrophic livestock losses in this region (Allington *et al.*, 2018; Tong *et al.*, 2017; Xu GC *et al.*, 2014). Xilingol possessed about 18,104 km^2 available pasture resources and $1240.4 \cdot 10^4$ sheep units at the end of 2015 (Xie & Sha, 2012). Around 1.044 million people lived in Xilingol in 2015, with ethnic Mongolian minorities accounting for around 31% and the rural population for 37% (Batunacun *et al.*, 2019; Shao *et al.*, 2017). Xilingol is a vast grassland, known for its high-quality meat products, nomadic culture, rich mineral resources and ethnic minorities. The ongoing degradation of grassland is receiving increasing attention. A set of economic stimuli and ecological protection policies launched in Xilingol were viewed as the root cause of GD over the past four decades. Although large-scale ecological restoration policies were implemented after 2000 in a bid to reduce GD, the problem still persists.

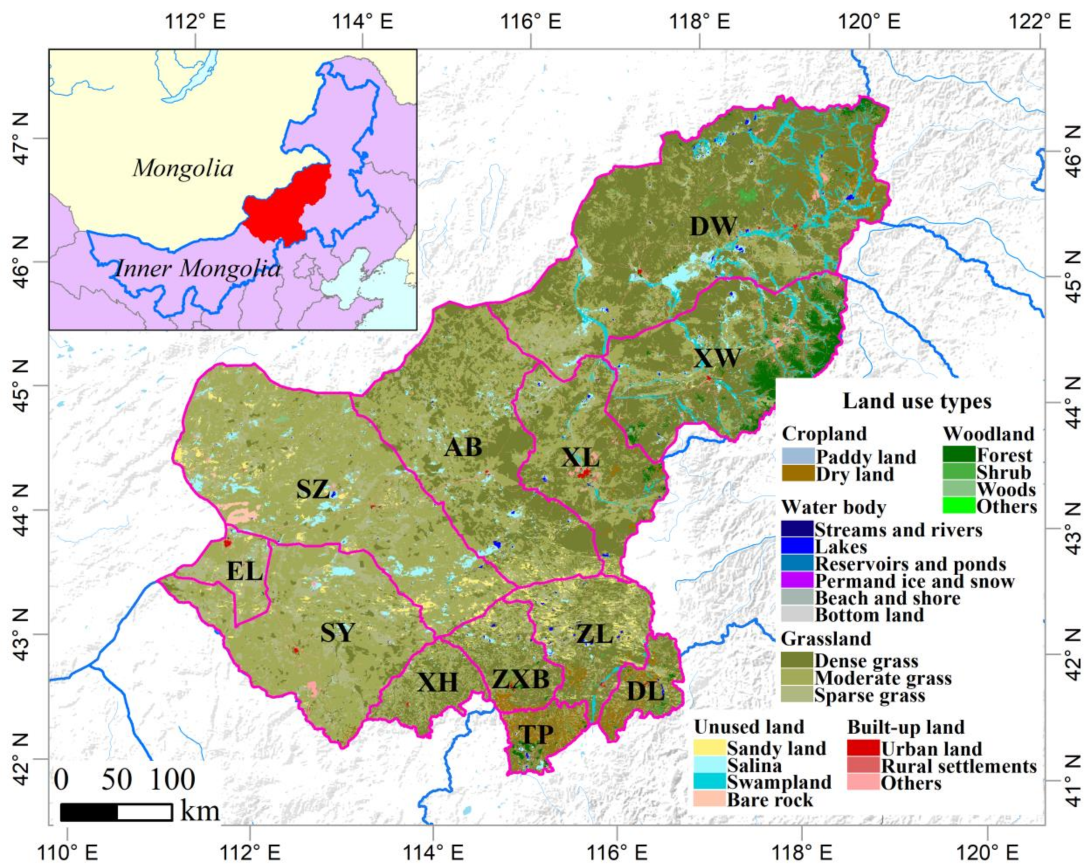


Figure IV-1: The location of the Xilingol League in Inner Mongolia and its land uses.

2.2 Grassland degradation

This study defines grassland degradation (GD) based on land-use conversion, involving two kinds of land-use change processes: (i) the complete destruction of grassland by transformation to another type of land use (built-up land, cropland, woodland, water bodies and unused land), and (ii) a decline in grassland coverage, which includes dense grass deteriorating into moderately dense grass and sparse grass, and moderately dense grass deteriorating into sparse grass (see Figure SI IV-1a). Given that GD is a dynamic process, we intended in this study to find the major drivers of newly added grassland degradation (NGD). NGD refers to the difference in spatial GD extent between two periods. About 13.0% of the total grassland area (176,410 km^2 in 2015) was degraded between 1975 and 2000 (Figure SI IV-1b); a further 10.6% was degraded in 2000-2015 (Figure SI IV-1c). Comparing the two periods, approximately 10.2% of the grassland corresponded to the NGD area across the whole region (Figure SI IV-1d). 18,093 pixels were extracted from the total NGD area, while the pixel number of conversion for other land uses is 178,990 in this study (hereafter: non-NGD).

2.3 Data collection

In line with previous studies, a checklist of possible drivers (D) of GD was developed from the literature (Cao *et al.*, 2013; Sun *et al.*, 2017). A total of 19 drivers were grouped into four categories (see Table IV-1). All categories were described as follows: (1) Climate factors, including the annual mean temperature (T) and annual sum of precipitation (P) in the growing season (April to Sep), were extracted from the longest available weather dataset (from 1958-2015), in combination with evaluation data and the kriging algorithm, to produce 1×1 km^2 raster files. (2) Geographic factors include elevation (DEM), and slope and aspect (extracted from DEM data), which can be treated as the characteristic of each grid cell. The DEM data were extracted from the SRTM 90m resolution and, after resampling, all data were processed into 1×1 km^2 raster files. (3) Distance measures (the distance of each pixel centre to urban, rural, road and mining, forest, cropland, dense grass, moderately dense grass, sparse grass and unused land pixels) are widely used factors for different land-use models (Khoury, 2012; Samardžić-Petrović *et al.*, 2016, 2017; Zhang *et al.*, 2013). All distance measures were extracted from LUCC datasets from the years 2000 and 2015 using ArcGIS Euclidean distance, and processed into 1×1 km^2 grids. (4) Socio-economic factors include the gross domestic product (GDP), sheep density and population density from 2000 and 2015. GDP and population density were obtained from a resources and environment data cloud platform, CAS (http://www.resdc.cn/); sheep density data were accessed from statistical data; and we converted all livestock data into grassland pixels. (5) Finally, we identified an area in which we assumed a strong policy impact in the past, and developed a proxy for the policy effect on grassland degradation. Here, a range of ecological protection measures were implemented inside and outside the Hunshandake and Wuzhumuqin sand lands (see Table IV-1), e.g. a livestock ban and the promotion of chicken farming (Su *et al.*, 2015). In a bid to explore policy effects, we assumed that GD is effectively slowed down by various policies inside the sandy area (proxy set as 0), while outside the sandy area, land degradation is more likely to happen in the absence of any policy effect (proxy set as 1, see Figure SI IV-2).

Table IV-1: Definition and derivation of drivers

Code	Name of driver	Definition of driver	Unit	Measures	Time series	Original format	Process approach	Data sources
Climate factors								
F1	temperature	Difference between average temperature / total precipitation in growth season (April-September)in Phase 1* and Phase 2*	°C	Mean temperature	2000, 2015-2030	Grid	Kriging via ArcGIS and Python language	National Meteorological Information Center (https://data.cma.cn/)
F2	precipitation		mm	cumulative rainfall	2000, 2015-2030			
Geographic factors								
F3	DEM	DEM	m	--		Grid	--	STRM
F4	slope	slope	degree	--		Grid	Reclassification	http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp
F5	aspect	aspect	degree	--		Grid	Reclassification	
Distance measures								
F6	discrop	Change of distance to cropland in 2000 and 2015	m	Distance	2000, 2015	SHP	Euclidean	Extraction from land-use data
F7	disforest	Change of distance to forest in 2000 and 2015	m	Distance	2000, 2015			
F8	disunused	Change of distance to unused land 2000 and 2015	m	Distance	2000, 2015			
F9	disdense	Change of distance to dense grass 2000 and 2015	m	Distance	2000, 2015			
F10	dismode	Change of distance to moderate grass in 2000 and 2015	m	Distance	2000, 2015			
F11	dissparse	Change of distance to sparse grass 2000 and 2015	m	Distance				

F12	disurban	Change of distance to urban in 2000 and 2015	m	Distance	2000, 2015			
F13	disrural	Change of distance to rural in 2000 and 2015	m	Distance	2000, 2015			
F14	disroad	Change of distance to road in 2000 and 2015	m	Distance	2000, 2015			
F15	dismine	Change of distance to mining in 2000 and 2015	m	Distance	2000, 2015			
F16	diswater	Change of distance to water in 2000 and 2015	m	Distance	2000, 2015			
Social-economic factors								
F17	population density	Change of population density in 2000 and 2010	Person	Person/ km^2	2000, 2010	Grid	Density	Resource and Environment data cloud platform, CAS. (http://www.resdc.cn/)
F18	GDP*	Change of GDP in 2000 and 2010	Yuan	Yuan/km^2	2000, 2010	Grid	Density	
F19	sheep density	Change of sheep density in 2000 and 2015	Sheep Unit	Sheep unit/km^2	2000, 2015	Grid	Density	Statistical data from Xilingol government website (http://tjj.xlgl.gov.cn/)
Scenario setting								
F20	policy	--	--	(0,1)	--	Grid	--	Assumption

*Note: Phase 1 refers to 1975-2000; Phase 2 refers to 2000-2015. GDP: gross domestic product.

2.4 XGBoost and logistic regression

Two algorithms were selected in this study: logistic regression (LR) and XGBoost. LR is a linear method involving two parts: the statistic LR and the classification LR. Both methods have already been used to simulate land use (Lin *et al.*, 2011; Mustafa *et al.*, 2018) and to define the relationship between land-use change and its drivers (Gollnow & Lakes, 2014; Mondal *et al.*, 2014; Verburg *et al.*, 2002; Verburg & Chen, 2000). Here, we use LR as a benchmark model to compare linear and non-linear methods in the simulation of land-use change. The optimised parameters of LG are C = 0.1, penalty = l2, solver = 'lbfgs', multi_class = 'multinomial'.

Boosting algorithms have been implemented in many past studies, where they often outperformed other ML algorithms (Ahmadlou *et al.*, 2016; Filippi *et al.*, 2014; Freeman *et al.*, 2016; Keshtkar *et al.*, 2017; Tayyebi & Pijanowski, 2014). However, traditional boosting algorithms are often subject to overfitting (Georganos *et al.*, 2018). To overcome this problem, Chen and Guestrin (2016) presented a new, regularised implementation of gradient boosting algorithms, which they called XGBoost (eXtreme Gradient Boosting). XGBoost was built as an enhanced version of the gradient boosting decision tree algorithm (GBDT), a regression and classification technique developed to predict results based on many weak prediction models – the decision tree (DT) (Abdullah *et al.*, 2019; Freeman *et al.*, 2016). XGBoost provides strong regularisation by adopting a stepwise shrinkage process instead of the traditional weighting process provided by GBDT. This process limits overfitting, minimises training losses and reduces classification errors while developing the final model (Abdullah *et al.*, 2019; Hao Dong *et al.*, 2018).

The XGBClassifier uses the following parameters: learning_rate (controls learning itself); max_depth (control depth of the RF); the n_estimators (controls the number of estimators used for the model); the min_child_weight (controls the complexity of a model, defines the minimum sum of weights of all observations required in a child); and lambda (L2 regularisation term on weights). The parameters were optimised using a simple grid search algorithm provided by scikit (Pedregosa *et al.*, 2011) to estimate the optimal parameters (learning_rate = 0.1, max_depth = 9, n_estimater = 500, min_child_weight = 3, lambda = 10).

2.5 Sampling methods

Data are often distributed unevenly among different classes (Vluymans, 2019). Such imbalanced class distribution generally induces a bias. Canonical ML algorithms assume that data is roughly balanced in different classes. In real situations, however, the data is usually skewed, and smaller classes often carry more important information and knowledge than larger ones (Krawczyk, 2016). It is therefore important to develop learning from imbalanced data to build real-world models (Krawczyk, 2016; Vluymans, 2019). To ensure a highly accurate GD model, we introduced four different sampling methods in this study (Figure SI IV-3).

Balanced sampling: Random data sampling, resulting in equal sized samples.

Imbalanced sampling: Random data sampling, but with the same share of the sampled class, resulting in unequal sized samples.

Over-sampling: Artificial points are added to the minority class of an imbalanced sampling set, making it equal to the majority class and resulting in equal sized samples.

Under-sampling: Points are removed from a majority class of an imbalanced sampling set, making it equal to the minority class and resulting in equal sized samples (He & Garcia, 2009).

In the present study, we used these four sampling methods to evaluate the model in the context of the sampling method and its performance in the training process and the simulation process (see Figure SI IV-3). In our case study, 18,190 pixels (about 10% of the total) were selected by different sampling methods (Figure SI IV-3) to train (66% of the sample size) and test (34% of the sample size) the model.

2.6 SHAP values

SHAP (SHapley Additive exPlanations) is a novel approach to improve our understanding of the complexity of predictive model results and to explore relationships between individual variables for the predicted case (Lundberg & Lee, 2017). SHAP is a useful method to sort the driver's effects, and break down the prediction into individual feature impacts. Feature selection is of primary concern when using ML methods to process land-use change (Samardžić-Petrović *et al.*, 2015, 2016, 2017). SHAP values show the extent to which a given feature has changed the prediction, and allows the model builder to decompose any prediction into the sum of the effects of each feature value and explain – in our case – the predicted NGD probability for each pixel (see Figure IV-2). In this study, we used SHAP values to sort the driver's attributions; capture the relationship between drivers and NGD; and map the primary driver for NGD at the pixel level.

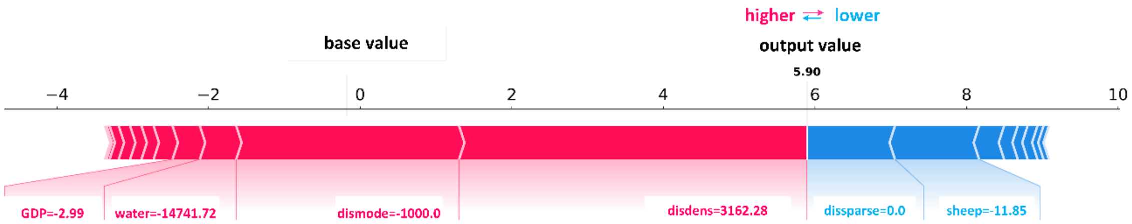


Figure IV-2: Decomposed SHAP values for the individual prediction of an example pixel.

In our study, we define the *base value* as the value that would be predicted by the model if no feature knowledge were provided for the current output (mean prediction); we define the output value as the prediction for this particular observation. SHAP values are calculated in log odds. Features that increase the value of the prediction (to the left in Figure IV-2) are always shown in red; those that lower the prediction value are shown in blue (to the right in Figure IV-2, Dataman, 2019). In this instance (Figure IV-2), *disdense* (change of distance to dense grass) is the primary driver of NGD at this pixel level (largest value). The fact that the value is positive means that the risk of NDG increases in line with an increase in distance to dense grass areas.

2.7 Validation of the model

Two validation steps are required for ML models: validation of the training process, and validation of the simulation process. For the training process, a robust model was selected using overall classification accuracy, precision, recall and the kappa index. Accuracy, precision and recall were calculated based on a confusion matrix (CM， see Table IV-2) (He & Garcia, 2009). For the simulation process, the final model was validated using the kappa index, the area under the precision-recall curve, and recall. The validation indicators are defined as follows.

Overall classification accuracy (ACC) is the correct prediction of NGD and other pixels in the whole region. This indicator was used to evaluate the accuracy of the model. Precision is the proportion of correctly predicted positive examples (refers to NGD in this study) in all predicted positive examples. Recall is the proportion of correctly predicted positive examples in all observed positive examples (the observed NGD) (Sokolova & Lapalme, 2009). In general, high precision predictions have a low recall, and vice versa, depending on the predicted goals. Here, since we focus on NGD and other land-use changes, we use both indicators to evaluate our models.

Table IV-2: Confusion matrix for binary classification of newly added grassland degradation (NGD) and other changes, including four indicators: false positives (FP), cells that were predicted as non-change but changed in the observed map; false negatives (FN), cells that were predicted as change, but did not change in the observed map for disagreement; true positives (TP), cells that were predicted as change and changed in the observed map; and true negatives (TN), cells that were predicted as non-change and did not change in the observed map for agreement.

<table>
<tr><td rowspan="6">Simulated values</td><td colspan="4">Observed values</td></tr>
<tr><td></td><td>Others</td><td>NGD</td><td></td></tr>
<tr><td rowspan="2">Others
NGD</td><td>True negatives (TN)</td><td>False positives (FP)</td><td rowspan="2">Recall=TP/(TP+FN)</td></tr>
<tr><td>False negatives (FN)</td><td>True positives (TP)</td></tr>
<tr><td></td><td colspan="2">Precision =TP/(TP+FP)</td><td></td></tr>
<tr><td></td><td colspan="2">ACC=(TP+TN)/(TP+FN+FP+TN)</td><td></td></tr>
</table>

The precision-recall curve (PR curve) provides more information about the model’s performance than, for instance, the Receiver Operator Characteristic curve (ROC curve), when applied to skewed data (Davis & Goadrich, 2006). The PR curve shows the trade-off of precision and recall, and provides a model-wide evaluation. The area under the PR curve (AUC-PR) is likewise effective in the classification of model comparisons. The baseline for the PR curve (y) is determined by positives (P) and negatives (N). In our study, y = 0.09 (y = 18374/200652), which means when AUC-PR = 0.09, the model is a random model (Brownlee, 2018; Davis & Goadrich, 2006).

The kappa index (κ) is a popular indicator used to measure the proportion of agreement between observed and simulated data, especially to measure the degree of spatial matching. When $\kappa > 0.8$, strong agreement is yielded between the simulation and the observed map; $0.6 < \kappa < 0.8$ describes high agreement; $0.4 < \kappa < 0.6$ describes moderate agreement; and $\kappa < 0.4$ represents poor agreement (Landis & Koch, 1977).

In this study, κ was used to evaluate the agreement and disagreement between observed NGD and simulated NGD. Kappa should be the primary validation measure, followed by AUC-PR (used to evaluate model performance) and recall (used to evaluate model sensitivity). Features and definitions of these indicators are given below.

2.8 The structure of the ML model

The ML methodology of simulating GD involves six steps (Figure SI IV-4): (1) Target definition and data collection and processing; the targets of this study are to build a robust ML model for simulating NGD, as well as visualising these complex relationships between various variables and the dynamics of GD. A total of 20 drivers (D) of GD were collected. All dynamic drivers were processed by GIS into raster files and exported into ASCII files as final inputs for the ML model. (2) Data organisation: the ML model simulates land-use change as a classification task (Samardžić-Petrović *et al.*, 2015, 2017). In the present study, we organise this task as a binary classification Y (value 1 and 0, stand for NGD and Non-NGD); related drivers are x ($x_1, x_2, x_3 \ldots\ldots x_n$), n is the driver identifier, and x denotes the change in value of each driver. The process of data standardisation is usually necessary for most ML models, but since XGBoost is a tree-based method, it does not require standardisation or normalisation. In this case, we performed standardisation only for the logistic regression model. (3) Data sampling: this is a necessary step to avoid overfitting or the loss of important information. The sampling method generally includes balanced and imbalanced sample strategies. In this study, we tested various balanced sampling strategies to identify the most suitable one. (4) Model building and selection: a ranking was used to find the best model in each specific case. In our study, we defined a model with $\kappa > 0.8$ and AUC-PR>0.09 as robust, while $0.6<\kappa<0.8$ and AUC-PR>0.09 represents an acceptable model. (5) Model validation and feature ranking: after tuning the model, the most robust model and the driver with most useful information are selected. (6). The last step is explaining the model and the simulation.

3 Results

3.1 Model validation

The XGBoost model outperformed the LG model in both training and simulation (Figure IV-3 and 4). The LG model seems to be an inappropriate model for understanding NGD in this case. XGBoost yielded robust results in both training and simulation, with indicator values almost entirely above 90%. Figure IV-3 indicates that XGBoost performed very well across all balanced sampling methods (over-sampling, under-sampling and balanced sampling, red rectangle in Figure IV-3) in the training process. Only the imbalanced sampling exhibited a slightly weaker performance in the training process. This is mainly due to the balanced sampling datasets, which provided more information for the model. In addition, the model was affected less than the imbalanced sampling method by the majority class or unchanged cells (Mileva Samardzic-Petrovic *et al.*, 2018).

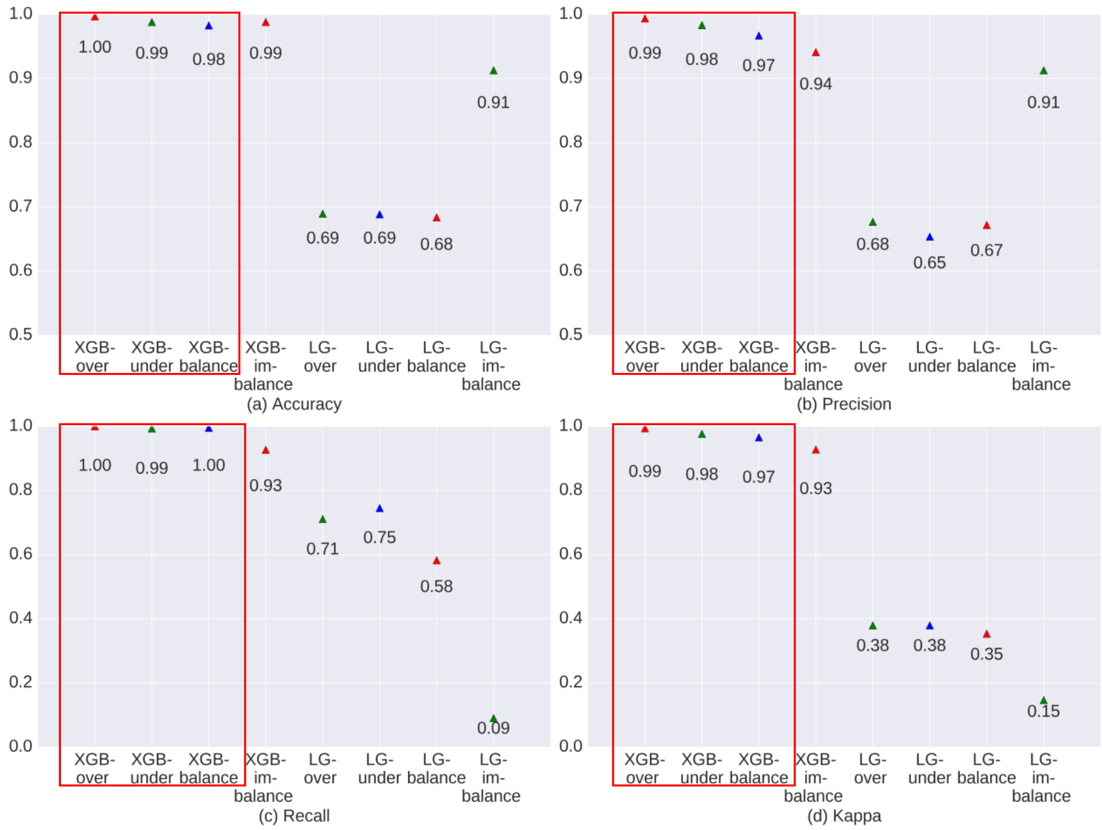


Figure IV-3: Evaluation of model performance during the training process.

Figure IV-4 and Figure IV-5 show the model evaluation results in the simulation process and the spatial prediction maps. XGBoost with under-sampling (green rectangle in Figure IV-4) yielded the weakest performance compared to the other three sampling methods. This is mainly due to the smaller sample size, which prevents the model from extracting sufficient experience. As can be seen in Figure IV-5b, XGBoost used with the under-sampling method produced the error map with the highest FP values, where the model predicted non-change points as change points. The under-sampling method is unable to identify NGD points sufficiently well. XGBoost used with the over-sampling method caused balanced and imbalanced sampling to have similar and strong prediction abilities (see Figure IV-4), differing only slightly in their CM indicators (see Figure IV-5). We finally selected XGBoost combined with the over-sampling strategy for our study, mainly because of its relatively higher values in κ, AUC-PR and recall (see Figure IV-4).

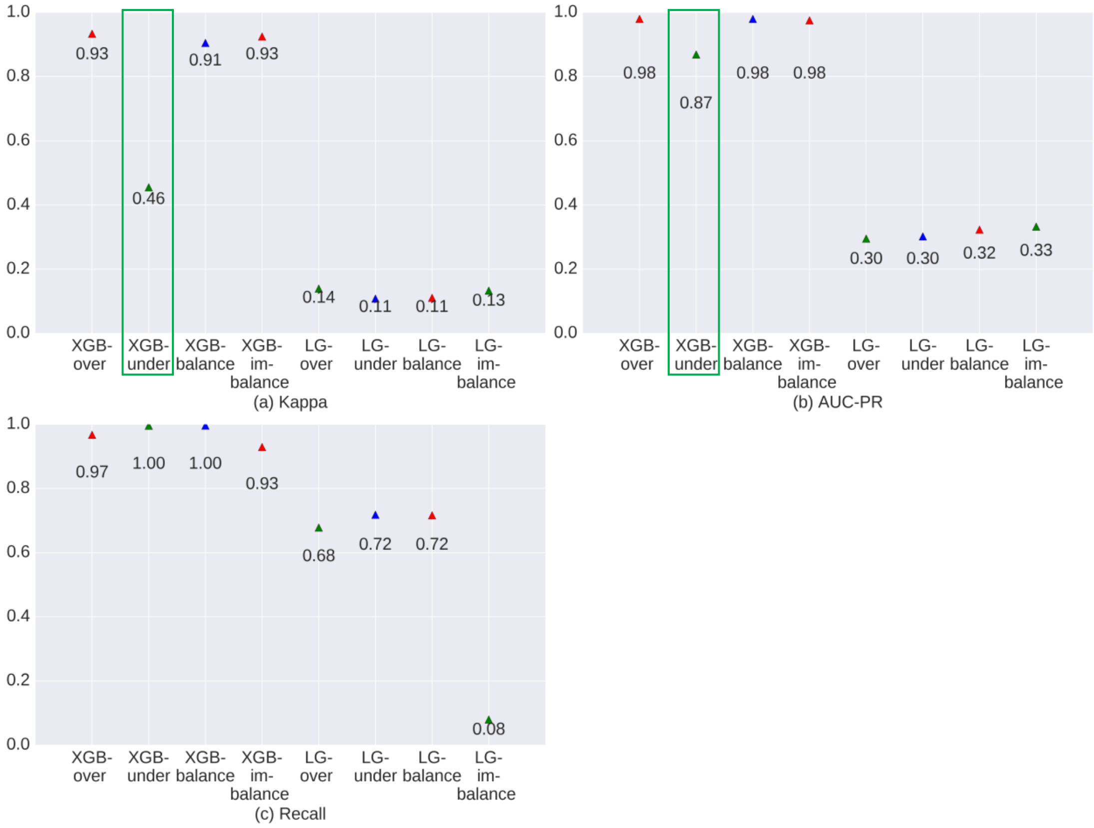
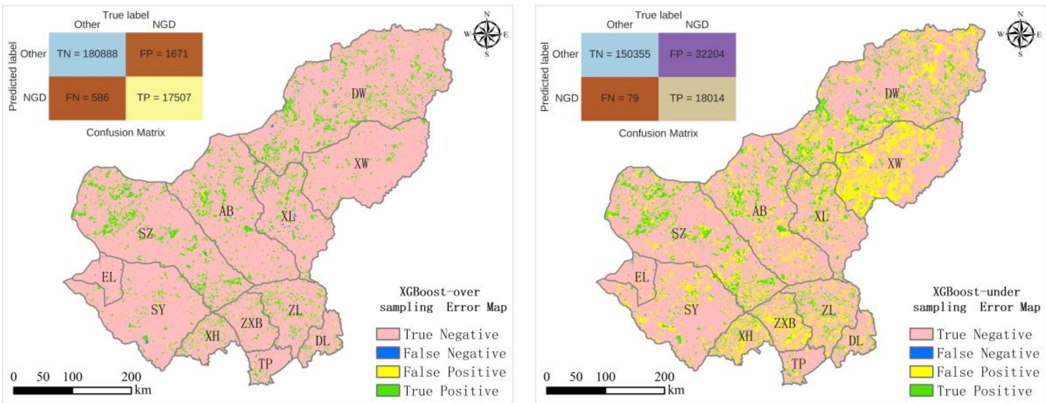
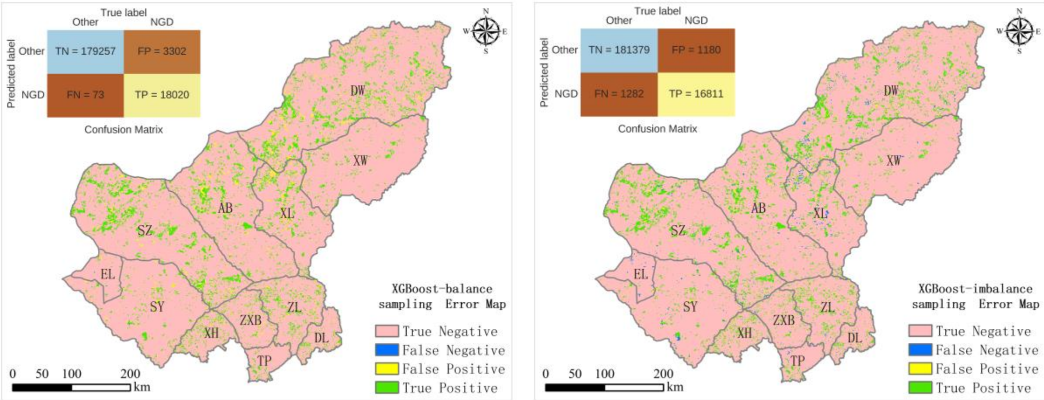


Figure IV-4: Evaluation of model performance during the prediction process.



(a) Over-sampling

(b) Under-sampling



(c) Balanced sampling (d) Imbalanced sampling

Figure IV-5: Error map of different sampling methods using the XGBoost model.

3.2 Driver selection

Figure IV-6 is a summary plot produced from the training dataset; it includes approximately 13,200 points (66% of the sample size). This plot combines feature importance (drivers are ordered along the y-axis) and driver effects (SHAP values on the x-axis), which describe the probability of NGD having occurred. Positive SHAP values refer to a higher probability of NGD. The gradient colour represents the feature value from high (red) to low (blue), as previously introduced in Figure IV-2. As Figure IV-6 shows, *disdense* was the primary driver for NGD in the study region. The relationship between *disdense* and NGD is non-linear, which can be seen from the SHAP values being both positive and negative (black rectangle in Figure IV-6). The interpretation of the effects of *disdense* can be summarised as a higher probability of NGD with increasing distance from dense grassland (see black rectangle in Figure IV-6 with pink colour on the right).

Figure IV-6 shows that driver effects include both linear-dominated relationships, such as *sheep*, *GDP* and others, and non-linear-dominated relations, such as *disdense*, *dismode* and others. In addition, the figure shows that the most important drivers for NGD are the changes of distance to dense, moderately dense and sparse grassland, then followed by sheep density and the distance to unused land. The effect of policies comes almost at the bottom, indicating that policies implemented outside sandy areas seem to have little effect on GD. The geographical factors DEM and slope are also positioned mid-field. The effect of geographical drivers does not appear to be as strong as the effect of other drivers. The change of distance to mining, located at the bottom for all drivers, does not have a strong effect on NGD compared to other drivers.

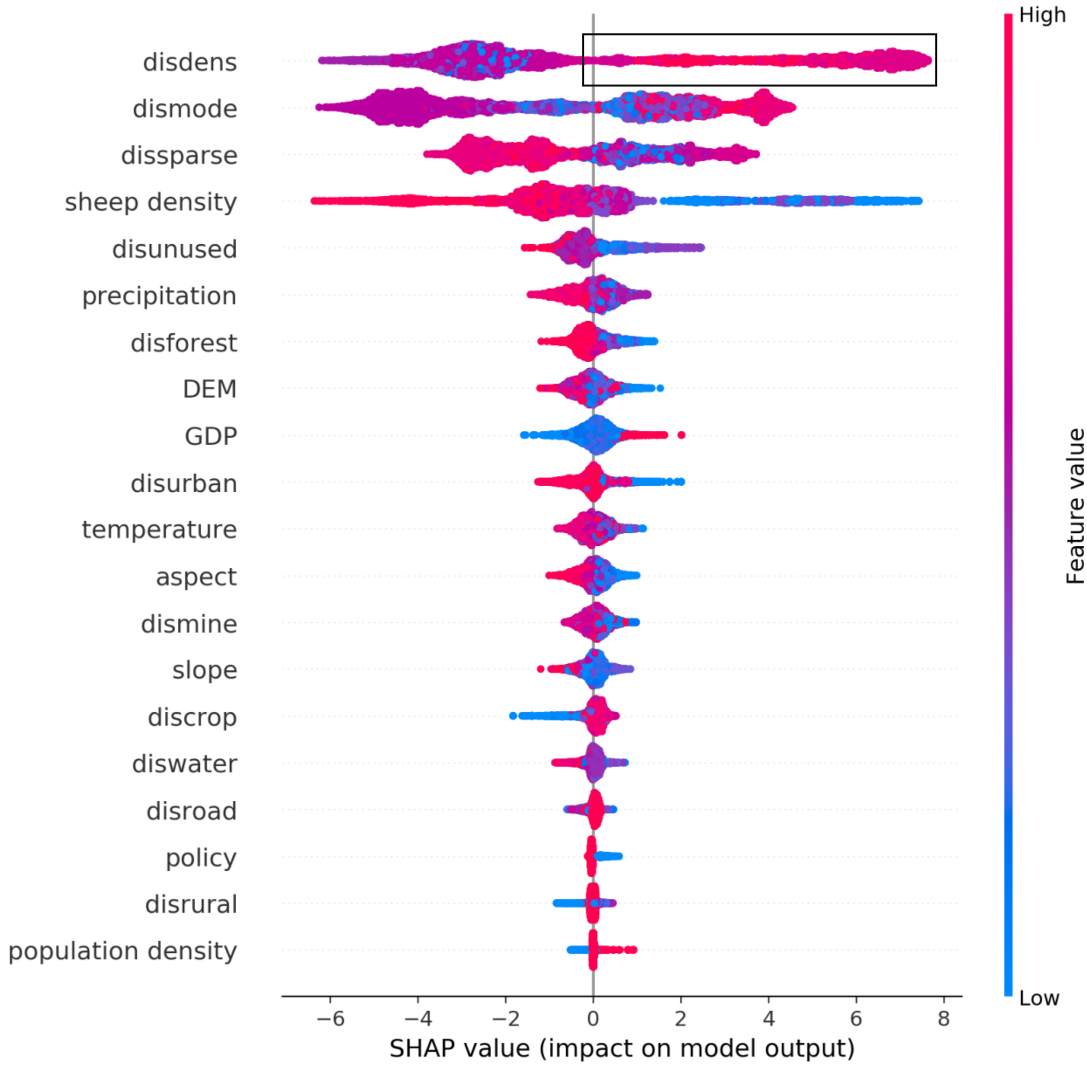


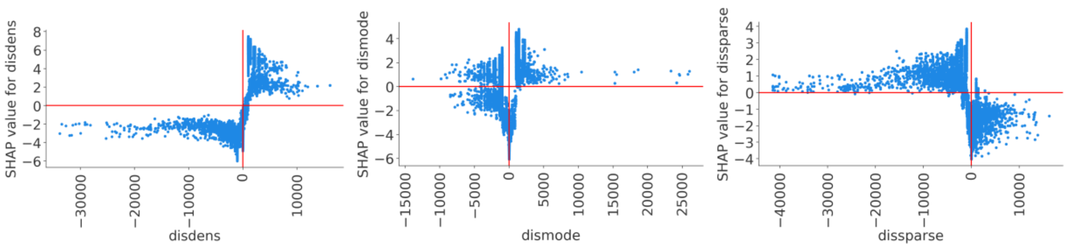
Figure IV-6: Driver ranking by SHAP values based on the training dataset (66% of sample size) using the over-sampling method.

Note: The top rank indicates the most significant effects across all predictions. Each point in the cloud to the left represents a row from the original dataset. The colour code denotes high (red) to low (blue) feature values. Positive SHAP values represent a higher likelihood of NGD, while negative values indicate lower likelihoods. The range across the SHAP value space indicates the degradation probability, expressed as the logarithm of the odds.

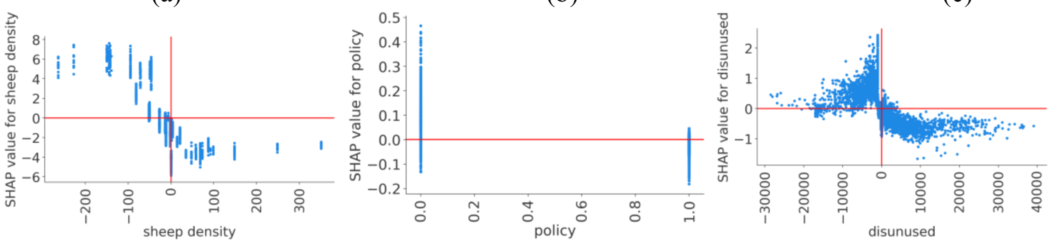
A recursive attribute elimination method was performed to determine how attribute reduction affects modelling performance using XGBoost with the oversampling method (see Figure SI IV-5; for more details, refer to Samardžić *et al.*, 2015). The results indicate that the first three drivers may already produce a satisfactory model ($\kappa = 0.74$, AUC-PR = 0.85, recall = 0.92), while adding the fourth driver can produce a robust model ($\kappa = 0.94$, AUC-PR = 0.98, recall = 0.98). This means that XGBoost used with the oversampling strategy can predict NGD with very high accuracy using a relatively small amount of data. Figure SI IV-6 shows the simulation result using the first four drivers, and compares the results with the observed map.

3.3 Relationship between NGD and drivers in the XGBoost model

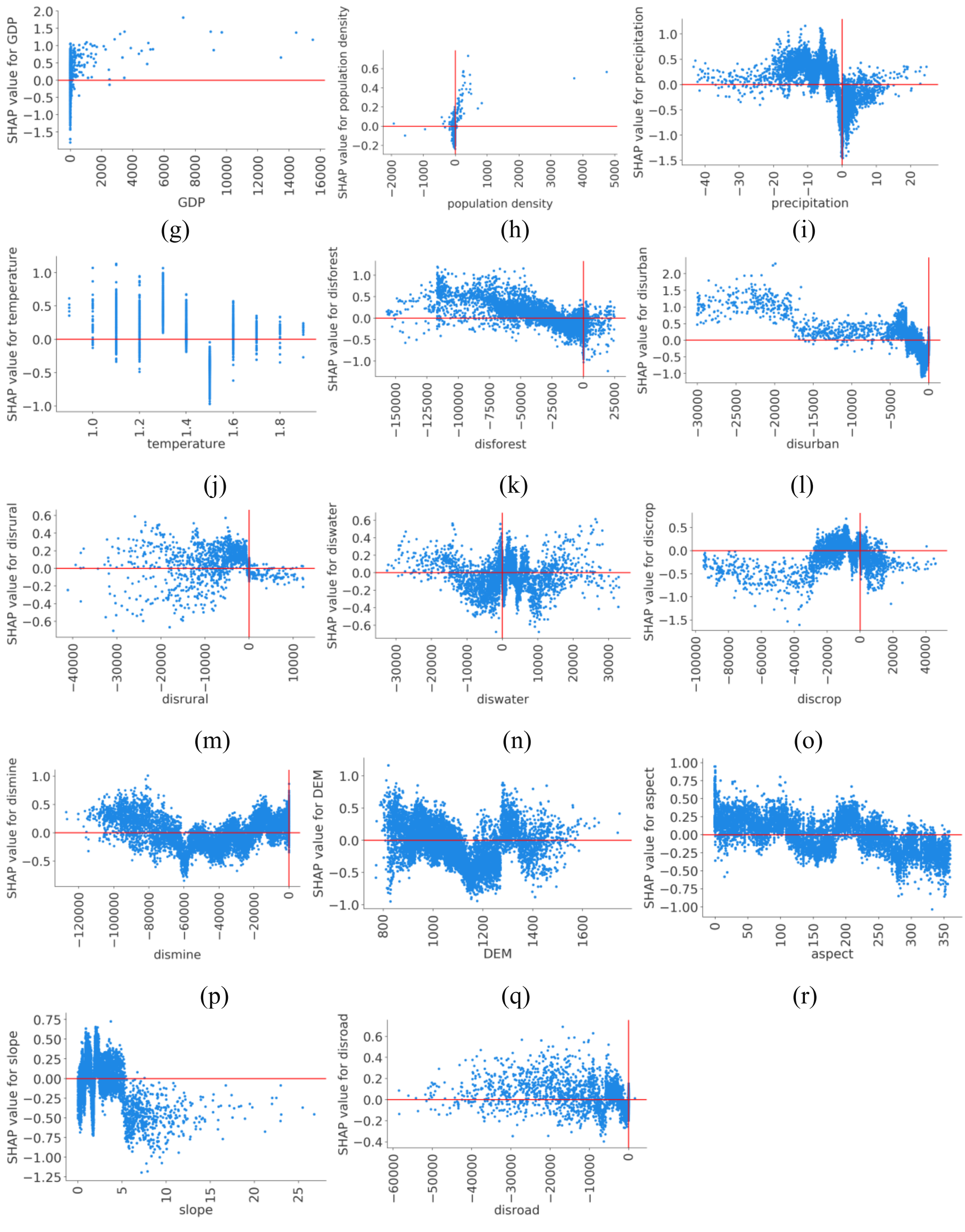
SHAP values and spread (Figure IV-7) indicate that no linear relationship between driver and prediction could be found for any of the individual features. Change of distance to dense, moderately dense and sparse grass pixels, and change of sheep density were the dominant drivers for NGD. Figure IV-7a indicates that when *disdense* < 0, the SHAP value is negative, and when the distance to dense grass areas is small, the likelihood of degradation is also small. The relationship seems to be more complex for distance to moderately dense grass (*dismode*, Figure IV-7b); here, no simple linear interpretation is obvious. For distance to sparse grass (*dissparse*, Figure IV-7c), the pattern again suggests a rather linear interpretation, which is that the likelihood of degradation increases with decreasing distance. For sheep density, Figure IV-7d indicates that when sheep density decreased, the probability of GD obviously increased. Policy was not identified as a major driver of GD (Figure IV-6). However, policy effects obviously have a different impact inside and outside sandy zones. Figure IV-7e shows that our initial assumption is invalid: the probability of GD increased inside the sandy areas where we assumed effective policy measures to be in place (value 0). This result is also in line with Figure IV-7g, which shows that the closer to unused land, the more likely degradation will occur. We can identify three groups for the remaining 14 drivers. For GDP and population density (Figure IV-7g and Figure IV-7h), the likelihood of NGD increases with increasing values. Figure IV-7i-j indicate that warmer and drier climate conditions increase the probability of GD. Figure IV-7k, l, m and n indicate that the probability of GD rises with closer distances to forest, urban, rural and water areas. Figure IV-7o shows a slight SHAP value pattern, in which the closer to cropland, the more unlikely degradation will occur. This is mainly due to transformation from cropland to grassland. Figure IV-7p-t do not show any interpretable spatial pattern.



(a) (b) (c)



(d) (e) (f)



(g) (h) (i)

(j) (k) (l)

(m) (n) (o)

(p) (q) (r)

(s) (t)

Figure IV-7: The SHAP dependence plot for each driver.

3.4 Mapping the primary drivers of NGD

All drivers' contributions to NGD were ranked according to their SHAP values for each pixel in this study. Figure IV-8 shows the primary driver for each NGD pixel. Distance to grassland pixels (dense, moderately dense and sparse grass) were the major drivers of NGD, responsible for 9,478, 3,892 and 1,629 NGD pixels, respectively. Sheep density was responsible for 3,042 NGD pixels, ranking third among all drivers. This order differs to that in Figure IV-6 and Figure SI IV-5 because in those cases, ranking is based on the total contribution of all drivers. Figure SI IV-7 shows the number of NGD pixels in which a driver was dominant or primary. The change of distance to any type of grassland was the primary driver for about 82.8% of the total NGD pixels; sheep density accounted for 16.8%. The remaining seven drivers caused less than 1% of the total NGD. We can see from the spatial pattern that the change of distance to grassland was the major driver for GD in the dense grassland region (counties of DW, XL and AB), while in the counties of SZ, SY, ZXB, ZL and TP, sheep density was often identified as the major driver.

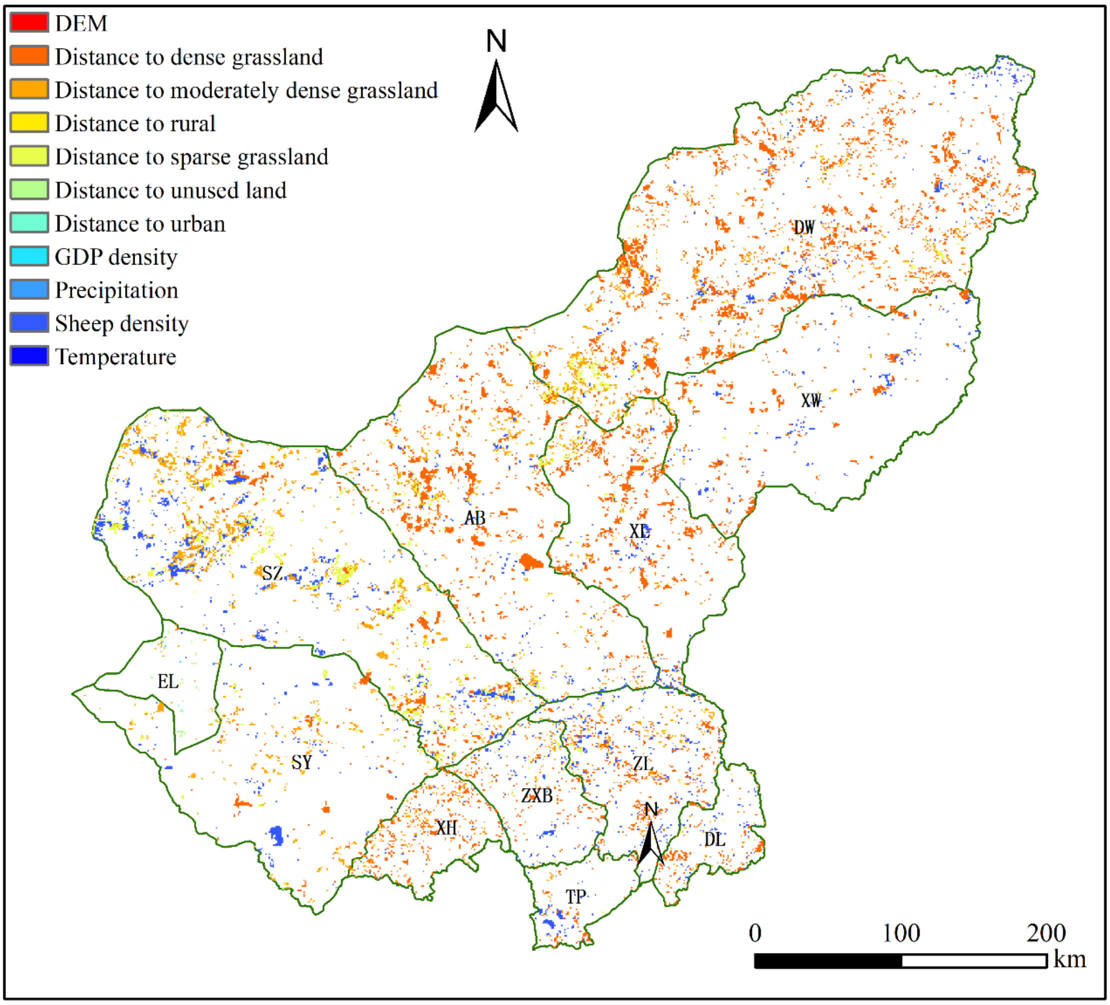


Figure IV-8: Spatial patterns of primary drivers for each pixel.

3.5 Regions of high risk for grassland degradation

A probability map of NGD was produced (Figure IV-9). Low probabilities of NGD were found in the central and northern counties (DW, XL, AB, SZ, ZL ZXB and XH), while high probability regions were EL, SY and XW. TP and DL in the south were categorised as low probability regions, due to their lower share of grassland area.

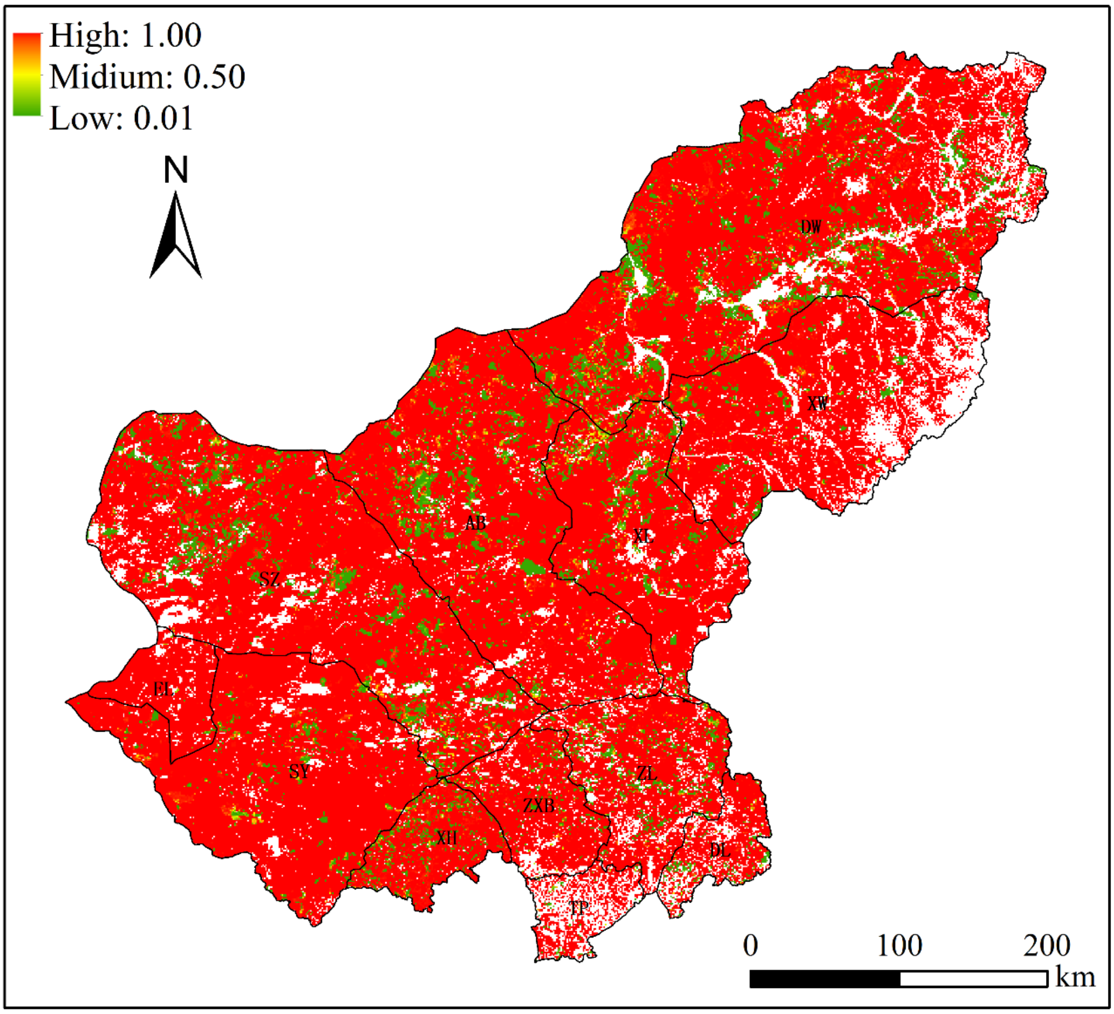


Figure IV-9: Degradation probability map for grassland in Xilingol.

4 Discussion

4.1 ML model building and evaluation

In this study, we defined a general framework for creating an ML model using the XGBoost algorithm for the purpose of analysing and predicting land-use change. XGBoost obtained a κ of 93% and a recall value of > 99% when used to simulate and predict GD in this study. Compared to other popular ML learning algorithms, XGBoost exhibited a strong prediction ability. In studies where ANN, SVM, RF, CART, Multivariate Adaptive Regression Spline (MARS) or LR were used in combination with Cellular Automata (CA), the recall value is usually 54%-60% (Shafizadeh-Moghadam *et al.*, 2017). Ahmadlou *et al.* (2019) stated that MARS and RF only yield high accuracy in training runs, but do not prove very accurate in the validating process when simulating land-use change.

Concerning the four sampling strategies we used to test the imbalance issue, we found that all strategies performed satisfactorily in the training runs. In the simulation, the under-sampling strategy yielded a relatively low accuracy ($\kappa = 0.46$) model. We assume that removal of data from the majority class causes the model to lose the important concepts pertaining to the majority class (He & Garcia, 2009). XGBoost used with the under-sampling method always produced similar results, irrespective of the size of the dataset (see Figure SI IV-8). We conclude from this pattern that XGBoost is also able to use sparse data to reflect real-world problems (Chen & Guestrin, 2016).

4.2 SHAP values and drivers of grassland degradation

The general idea of introducing SHAP values as a further tool to analyse XGBoost ranking is to provide a method to evaluate the ranking with respect to causal relationships. The original XGBoost ranking is based on the in-built feature selection functions *Gain* (refers to the improvement in accuracy provided by a feature), *Weight* (or frequency, refers to the relative number of a feature occurrence in the trees of a model) and *Coverage* (refers to the relative numbers of observations related to this feature). However, these functions always produce different rankings of drivers (Abu-Rmileh, 2019) due to random components in the algorithms. SHAP values introduce two further properties of feature importance measures: *consistency* (whenever we change a model such that it relies more on a feature, the attributed importance for that feature should not decrease) and *accuracy* (the sum of all feature importance values should equate to the total importance of the model; Lundberg, 2018; Lundberg & Lee, 2017). Consistency is required to stabilise the ranking throughout the analysis, reducing the change of order in the ranking to a minimum when the number of identified drivers changes. The accuracy property of SHAP makes sure that each driver's contribution to overall accuracy remains the same, even when drivers are excluded from analysis. Other methods usually compensate for the withdrawal of a driver from the analysis, which makes the determination of a single driver's contribution difficult.

The feature ranking based on SHAP values indicated that the change of distance to any type of grassland (dense, moderately dense and sparse grass) is the most important driver for any newly added grassland degradation. In this context, dense and moderately dense grassland areas are more easily degraded than other land-use types, followed by sparse grass. These results are in line with previous studies (Li *et al.*, 2012b; Xie & Sha, 2012). Good-quality grassland is more likely to be degraded through increasing human disturbance. An explanation for this can be derived from local people's living strategies. People who live in good-quality grassland areas are more likely to use grassland for livestock production with higher animal densities, risking overgrazing. Furthermore, Li *et al.* (2012) indicated that good-quality grassland is more likely to be converted to other land-use types, such as cropland. In contrast, people who have lived in sparse grassland regions for centuries have long adapted to low productivity, reducing their livestock numbers accordingly. They have also developed strategies to cope with variability in weather conditions, e.g. by preparing and storing more fodder and forage.

Sheep density was identified as the fourth major driver. However, the SHAP values indicate that when sheep density decreases, the probability of grassland degradation increases. Overgrazing has been the dominant driver for grassland degradation on the Mongolian plateau before, which has changed the grassland ecosystem significantly towards lower grass coverage (Nkonya *et al.*, 2016; Wang *et al.*, 2017). However, there is recent evidence that this causal relationship has changed. It now appears that farmers increasingly select their livestock numbers according to the carrying capacity of the grazing land (Tiscornia *et al.*, 2019, 2019). By passing the “Fencing Grassland and Moving Users” policy (FGMU), the Chinese government issued a law that regulates livestock numbers based on a previously calculated carrying capacity. This development has upturned the causal relationship between livestock numbers and NGD, reflected by the SHAP value pattern in Figure IV-6.

Besides the four main drivers, seven other drivers also occasionally appear as the main driver for some pixels (Figure IV-8). This highlights the fact that, at the local level, other drivers apart from the four drivers identified as being major can also play a significant role. For example, in the county of EL, the remaining seven drivers were mainly responsible for NGD. EL has less NGD after 2000 compared with other counties in Xilingol (Figure SI IV-1), and most of the EL area is covered by sparse grass. EL is the most frequented border control point to Mongolia, and is subject to intensive tourism.

In the sparse grassland and agro-pastoral regions (SZ, SY, ZXB, ZL and TP), sheep density was identified as the important driver. This indicates that, even though livestock numbers have decreased, grassland is still experiencing serious degradation in this region. Here we see additional potential for installing further grassland conservation measures, such as adjusting the livestock number to the grassland carrying capacity.

4.3 The current risk of grassland degradation in Xilingol

Three regions of different risk classes were identified in the probability map of NGD (Figure IV-9). The low-risk region (DW, XL, AB, SZ, ZL ZXB and XH) is dominated by good-quality grassland (dense and moderately dense grass). In recent decades, this region has suffered from increasing human disturbance, e.g. overgrazing and mining development. However, after 2000, grassland in this region has recovered, mainly as the result of ecological protection projects (Sun *et al.*, 2017). Even though this region is predicted as being less exposed to the risk of land degradation in the future, attention is still required for the restoration process. The high-risk region includes the counties of EL, SY and XW. EL and SY are covered by a large share of low-quality grassland, which – due to its own fragility – is likely to be affected by extreme climate and human disturbance, more than, e.g. higher-quality grasslands. The recent change in grassland property rights and the establishment of ecological protection projects have also limited the mobility of nomadic herders throughout Xilingol. As a consequence, herders cannot easily change grazing spots if extreme weather occurs; they are then bound to have their cattle graze at the same spots, increasing the pressure on low-quality grasslands in particular (Qian, 2011). For a long time, fragile grassland remained in an equilibrium state with the extreme weather (frequent droughts, “dudz”) to which it was exposed, and with the nomadic livestock husbandry that the region’s inhabitants practised. However, when the property rights of grassland and livestock were changed from collective to private, the nomadic lifestyle was largely abandoned.

4.4 The limitations of XGBoost for scenario exploration

XGBoost has already scored top in a range of algorithm competitions in the data scientists community (Kaggle, 2019) due to its high accuracy and speed (Chen & Guestrin, 2016). ML models extract patterns from data, without considering any existing expert knowledge, which is why they are increasingly used to identify non-linear relationships (Ahmadlou *et al.*, 2016; Samardžić-Petrović *et al.*, 2015; Tayyebi & Pijanowski, 2014). However, ML models require specific data structures for each problem to which they are applied. In this study, we simulated grassland degradation in two different phases (1975-2000 and 2000-2015). All time series of driver data were organised as model inputs, while grassland degradation dynamics were organised as prediction targets. Although the model achieved high accuracy in predicting NGD in Phase 2, it was not possible to achieve acceptable results in simulating both Phase 1 and Phase 2 separately. Second, compared with conventional models, the XGBoost model cannot be easily transferred to other regions for the same research question. Models like CLUE-S and GeoSOS-FLUS have been widely used in different regions across the world (Fuchs *et al.*, 2017; Liang *et al.*, 2018b; Liu, 2017; Verburg *et al.*, 2002). When ML models are used in other regions, driver data must be collected and structures adapted. Thirdly, ML models always need to learn sufficiently before they are able to make predictions. This requires a sufficient amount of data covering historical periods or different land-use change patterns.

XGBoost alone is unable to project any scenarios of land-use change based on historical data. However, the methodology presented here can be applied to quantify alternative scenarios produced using other approaches, such as conventional, rule-based models (Verburg *et al.*, 2002) or cellular automata (Islam *et al.*, 2018; Shafizadeh-Moghadam *et al.*, 2017).

5 Conclusion

Machine learning and data-driven approaches are becoming more and more important in many research areas. The design and development of a practical land-use model requires both accuracy and predictability to predict future land-use change, a well-fitted model that reflects and monitors the real world (Ahmadlou *et al.*, 2019). The method framework presented here for building an ML model and explaining the relationship between drivers and grassland degradation identified XGBoost as a robust data-driven model for this purpose. XGBoost showed higher accuracy in training and simulation compared to existing ML models. Combined with over-sampling, it slightly outperformed in the simulation process. The simulated map has a high agreement with the observed values (kappa=93%).

We identified six basic steps that should be included in ML model building, and they are also similar for other research applications (Kiyohara *et al.*, 2018, 2018; Kontokosta & Tull, 2017; Subramaniyan *et al.*, 2018). However, different validation measures can be introduced in both the training process and the simulation process. In this study, we tested different evaluation measures to evaluate the ML model, e.g. a typical confusion matrix to evaluate the training process, AUC-PR to evaluate the goodness of the ML model, and the kappa index to measure the degree of matching between observed and simulated values. These validation indicators consider both the research object and data characteristics. For example, when the data size is unbalanced, AUC-PR is a better choice than AUC-ROC (Brownlee, 2018; Davis & Goadrich, 2006; Saito & Rehmsmeier, 2015).

SHAP was introduced in this context to provide a causal explanation of the patterns identified by the ML model. In our case, SHAP was used to explain how drivers contribute to grassland degradation processes at the pixel and regional level, despite their non-linear relationship. According to the analysis, the distance to dense, moderately dense, and sparse grass, and sheep density, were the most important drivers that caused new grassland degradation in this region. In addition, individual SHAP values of sheep density indicated that the causal relationship between grassland degradation and livestock pressure has changed over time: the increase in sheep density was not the major driver for NGD in Phase 2 of the land degradation trajectory. Instead, the decrease in the grazing capacity of grassland caused a decrease in livestock numbers. The primary driver map of NGD provided a more detailed picture of NGD drivers for each pixel, as an important support for grassland management in the Xilingol region. The individual SHAP values of each driver may be an important prerequisite for rule-based scenario-building in the future.

Author contribution:

Batunacun prepared the manuscript with contribution from all co-authors, and Batunacun performed the simulation. Ralf Wieland developed the model code.

Code and data availability

The development of XGBoost and SHAP values, graphs and model validation presented in this paper were conducted in Python language. The python script and related data have been published at ZENODO and GitHub. Please check the link (https://zenodo.org/record/3937226#.Xw2M6egzZPY).

Competing interests:

The authors declare that they have no conflict of interest

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Supplementary Information

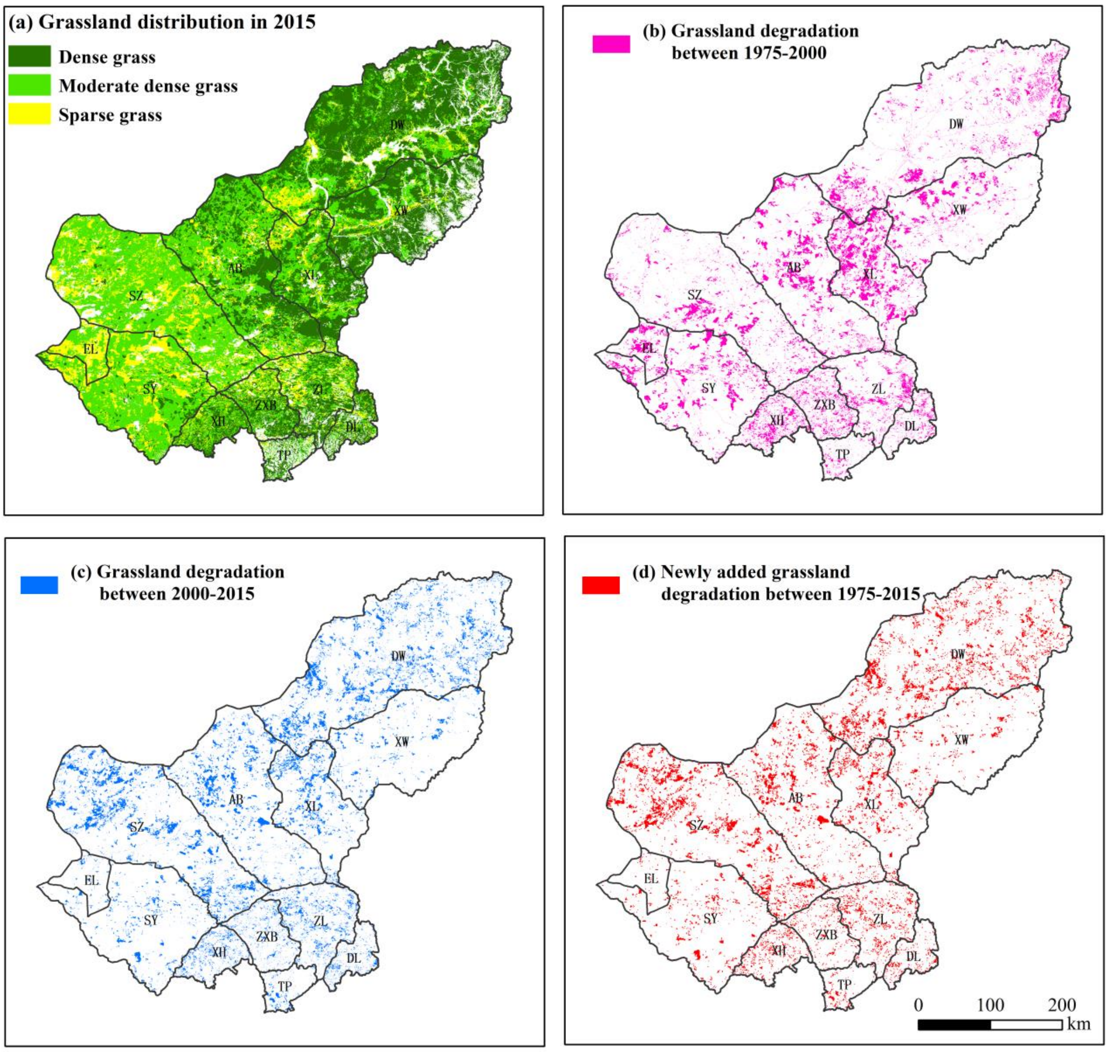

Figure SI IV-1: Land use change processes in 1975-2000 and 2000-2015

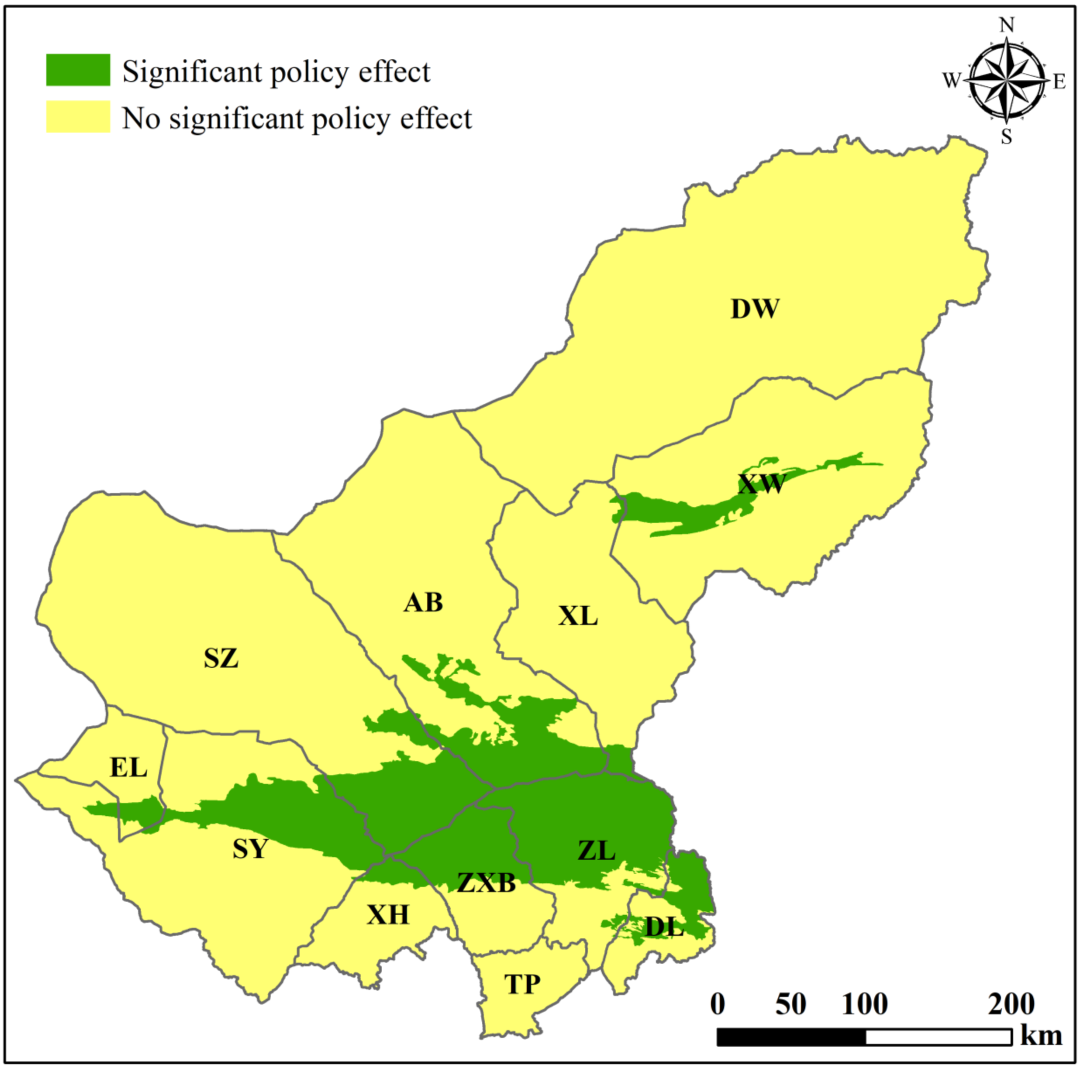

Figure SI IV-2: Policy scenario setting

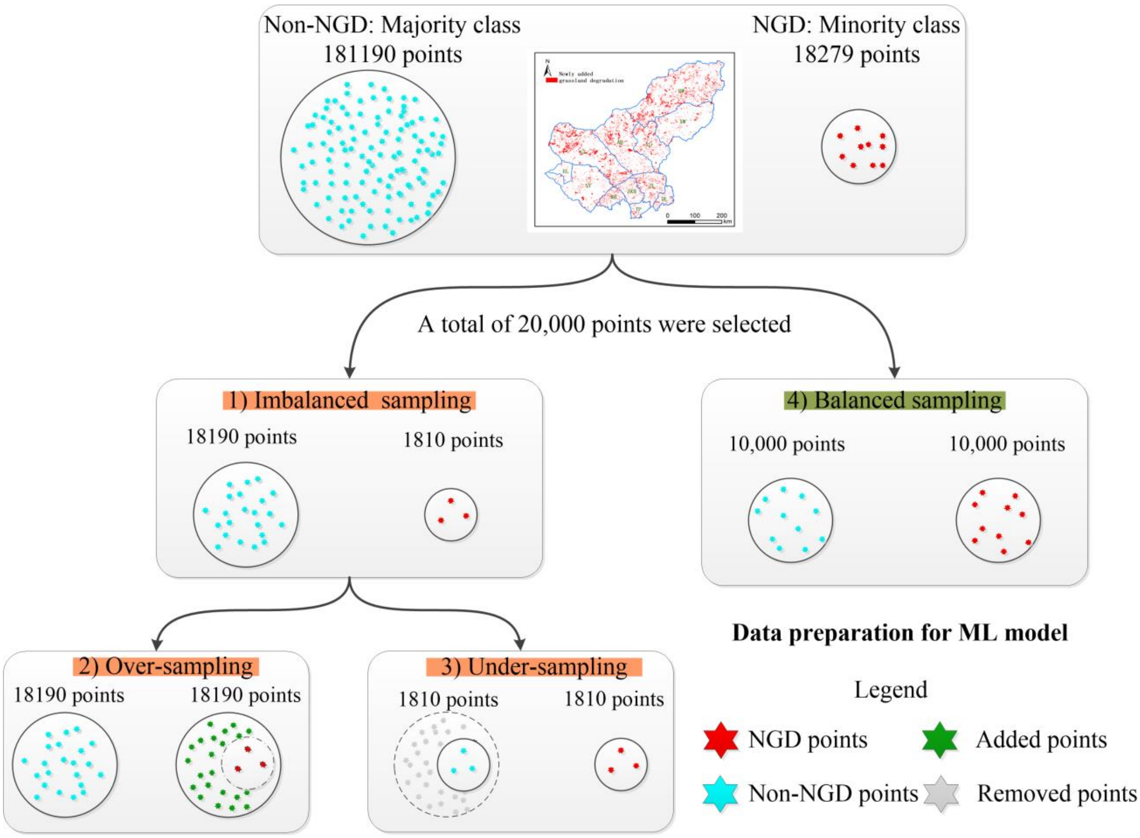

Figure SI IV-3: Data organisation and four sampling strategies

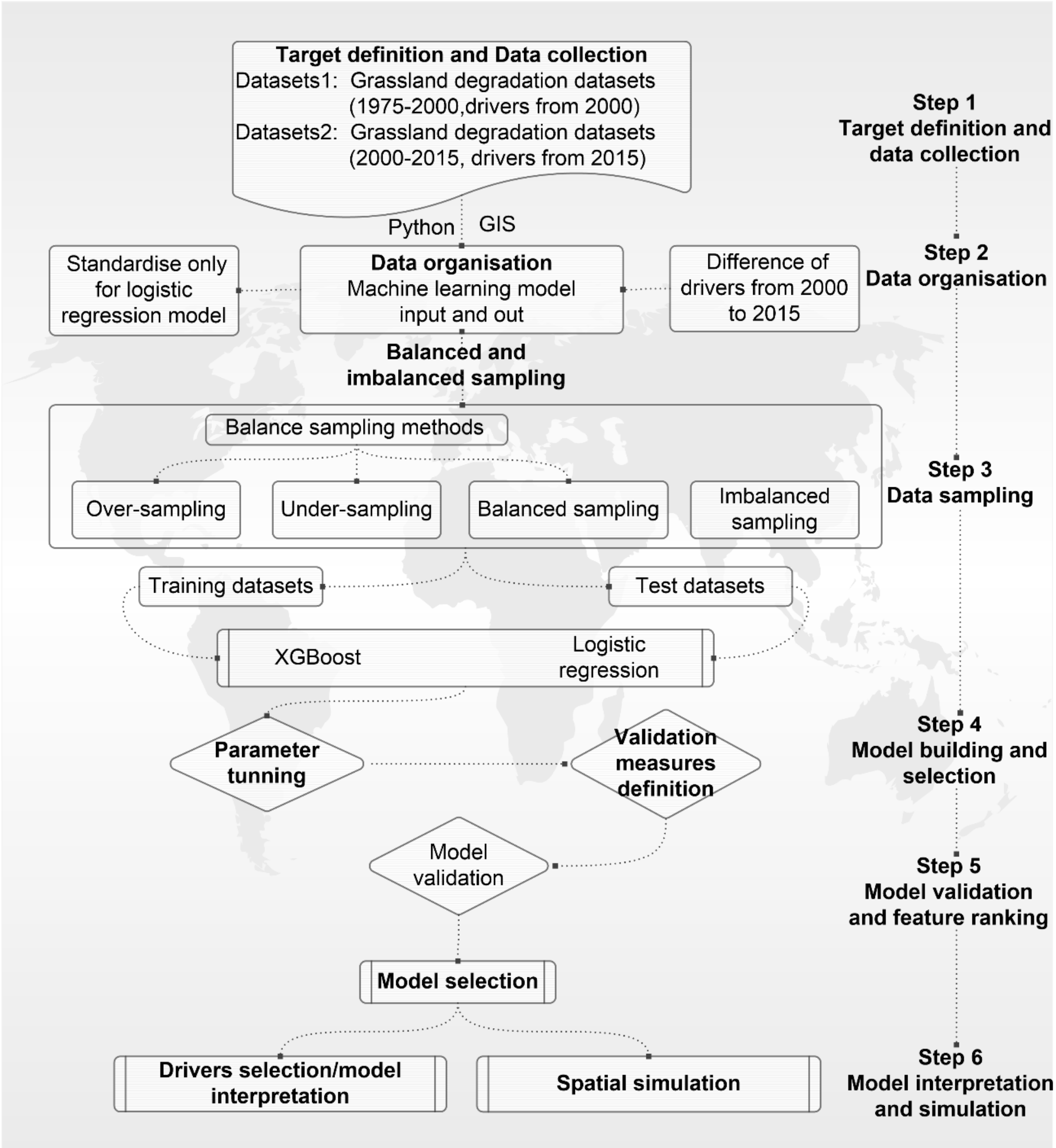

Figure SI IV-4: The workflow of the machine leaning in this study

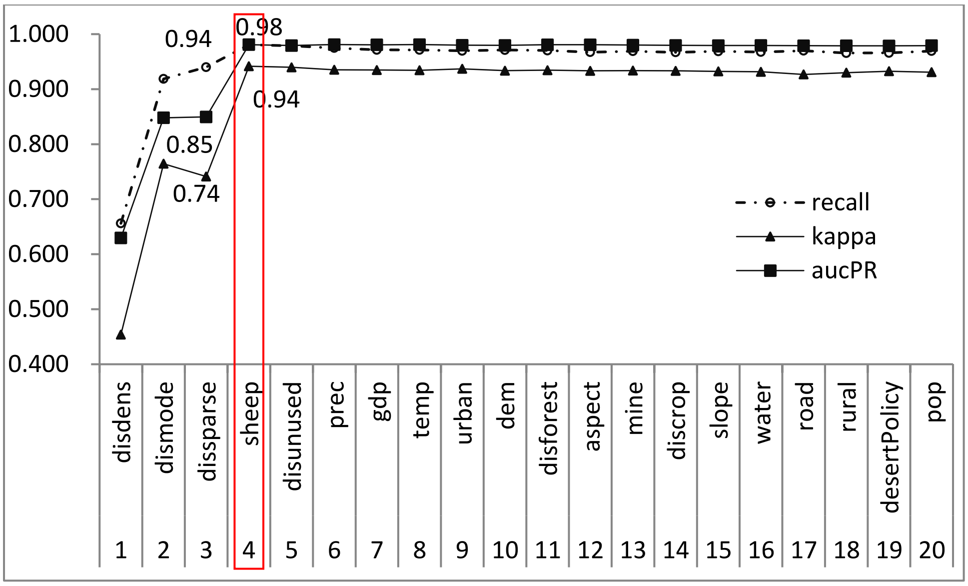

Figure SI IV-5: Obtained values for κ, Recall and ACC using recursive elimination method

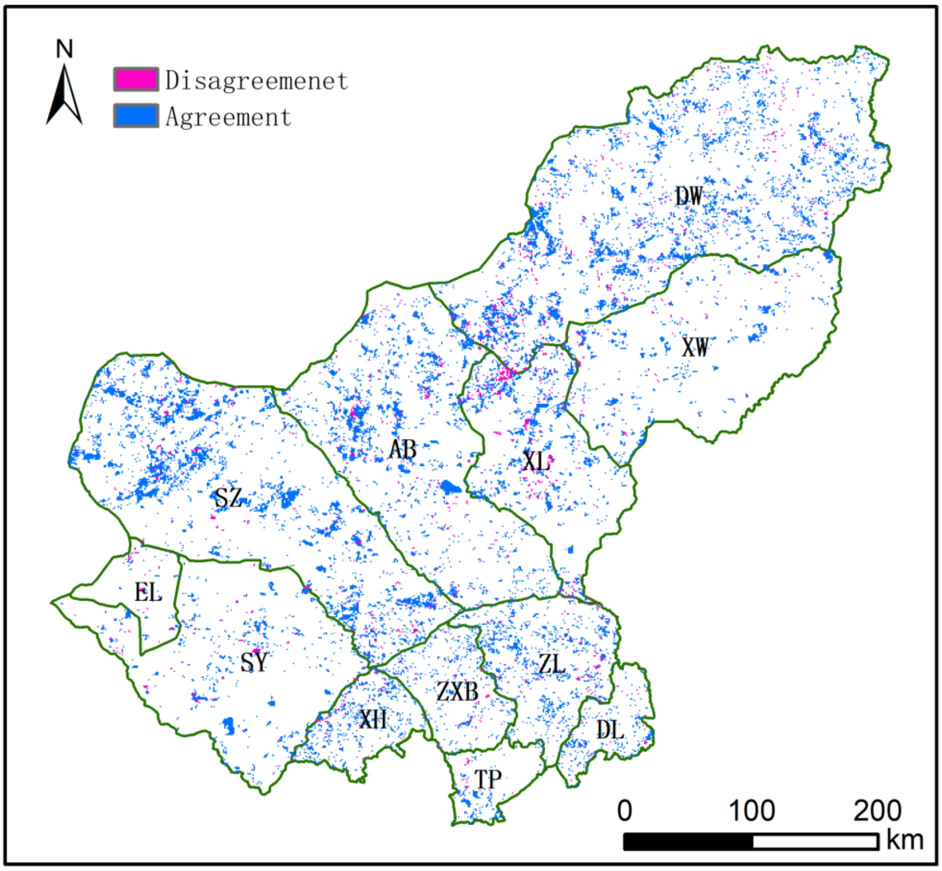

Figure SI IV-6: Maps of prediction results with top four drivers in Figure IV-6 and observed values

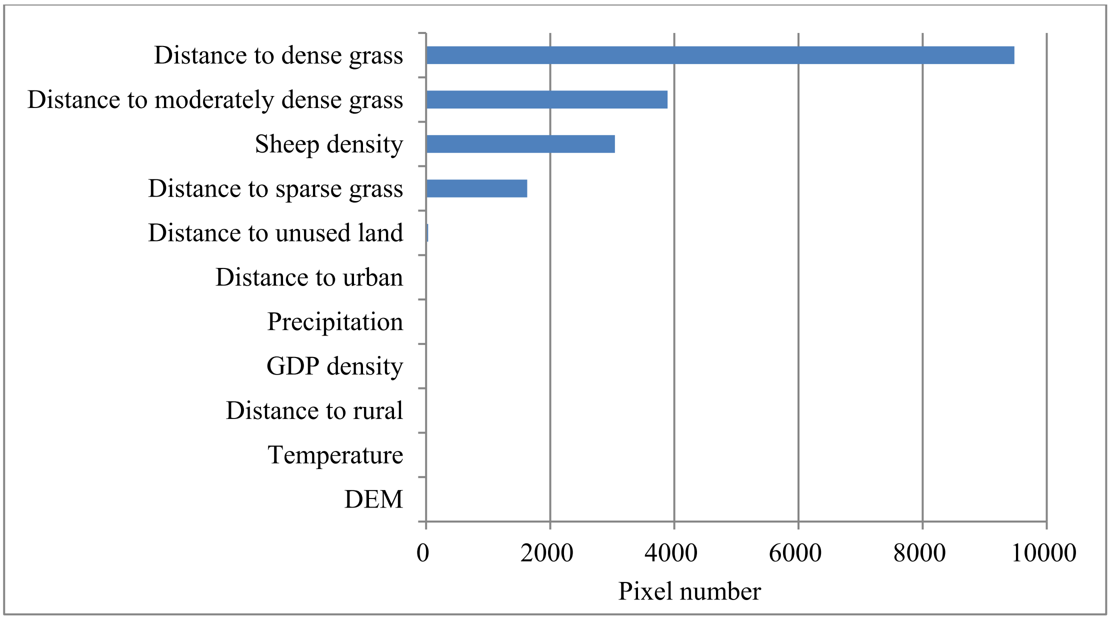

Figure SI IV-7: The number of pixels in which a driver is dominant. This analysis limited to only the primary drivers.

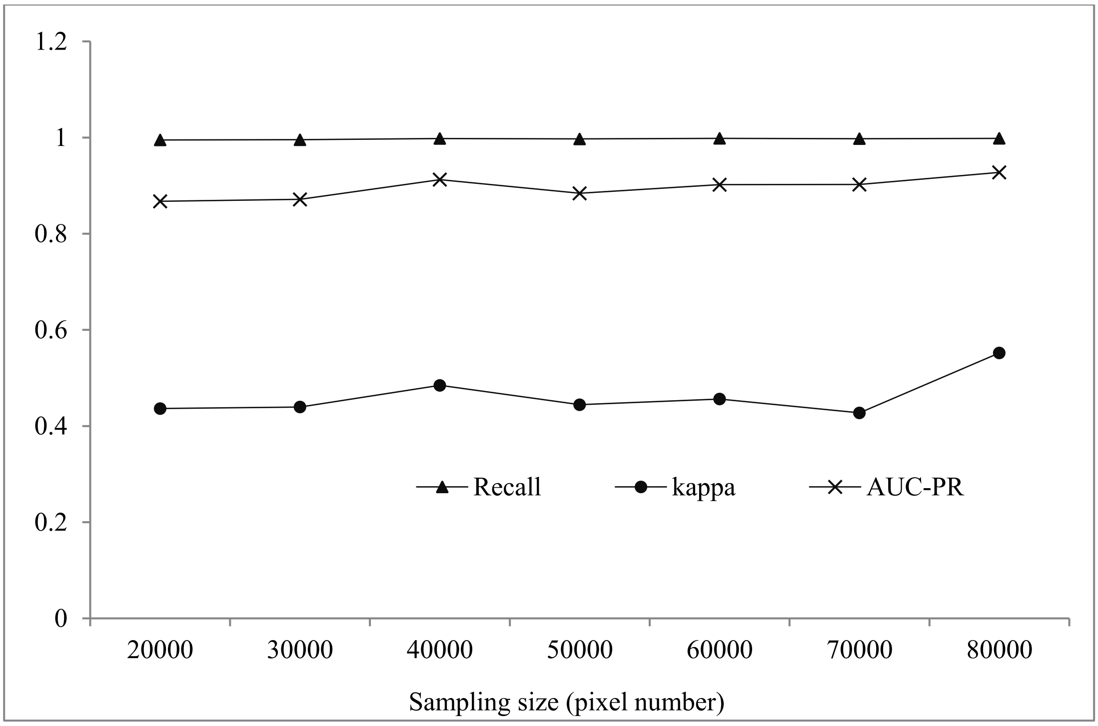

Figure SI IV-8: Under-sampling simulation results for different sampling size

Chapter V:
Synthesis

1 Summary

This thesis aims to provide an understanding of historical land use and land cover change over space and time on the Mongolian Plateau. Mongolia is a typical arid and semi-arid region that is covered by a major fragile ecosystem – grassland – and is sensitive to climate change and human disturbance. A comprehensive understanding of dramatic land use change on the Mongolian Plateau is crucial for achieving the sustainable development of global drylands. Throughout the world, drylands account for approximately 40% of the global land; at least 38% of the global population depend on drylands. Inner Mongolia, representing a major part of the Mongolian Plateau, has undergone an increasing amount of human disturbance in recent decades due to rapid economic development, a land tenure reformation, and overgrazing. In lights of this human disturbance, the region has experienced serious ecological degradation, with around 90% of its grassland having degraded to a certain degree. Consequently, ecological degradation has put severe pressure on the livelihoods and income of herders. It is a great challenge for governments to achieve a win-win situation in ecological aspects and economic development.

Ecological issues have been widely reported in the literature for the Mongolian Plateau. These include soil quality, climate change, policy transformation, changes in herders' livelihoods, grassland condition and human disturbance; all these factors have been well elaborated in theory. However, there are very few comprehensive and systematic studies that include an inventory of historical land use change and its drivers at different scales. Consequently, is was until now impossible to understand the complex relationship between degradation and its drivers. This thesis has integrated methods such as a geographical information system (GIS), remote sensing, a machine learning model, and partial order theory to explore historical land use change over space. In addition, two different cross-disciplinary methods were used to identify the major drivers of degradation at the county level, and to capture the complex relations between grassland degradation and its possible drivers at the pixel level.

Xilingol, a city located in the heart of Inner Mongolia, was chosen as a case study, mainly because of its specific landscape, geographical location and rich history. About 85% of the land in Xilingol is covered by natural grassland. Xilingol has the typical types of grassland that are representative of the entire Inner Mongolia, and even the north grassland region. Xilingol has an important geographical position because it acts as an important ecological protective barrier for Beijing. In addition, Xilingol has undergone almost all of the typical grassland-related policies, and experienced some very typical historical turning points, such as vast migration of the Han people, and considerable cropland expansion.

Three broad issues related to Xilingol are answered in three core chapters of this thesis.

<u>Research Question 1:</u> *How did land use/land cover and land degradation change in Xilingol between*

1975 and 2015?

Chapter II aimed at identifying patterns and processes of major land use and land cover change between 1974 and 2015 in a bid to evaluate land degradation, and especially grassland degradation processes, on the basis of LUCC analysis. Chapter II showed that dramatic land activities occurred in Xilingol in the period of 1975-2015; approximately 6.7% of the total land was radically converted. In addition, two distinct periods that were dominated by two different LUCC processes were identified. The first phase (1975-2000) was dominated by land degradation processes, the second phase (2000-2015) by land restoration processes. Correspondingly, a policy frame was summarised to analyse the possible root causes of these dramatic LUCC processes.

Built-up land and unused land increased significantly throughout the entire period, while grasslands and water bodies clearly decreased. Four major land use processes were identified in the first phase: cropland expansion; an increase in unused land; and increase in built-up land; and a decrease in grassland. This phase was dominated by land degradation processes; 11.4% of the total area was degraded, and land restoration accounted for only 5.39%. Since 1949, the property rights of grassland and livestock have been reformed radically, from collective to private, and vast numbers of the Han people have moved into grassland regions, stimulating economic development and resulting in overgrazing and widespread grassland degradation.

In the second phase, land rehabilitation dominated in this region, covering about 12.0% of the total area, but degradation still continued to account for 9.5%. In this period, the government installed a network of ecological construction engineers with the aim of improving grassland conditions and herders' income. These ecological projects were effective to some extent, and degraded grassland is able to recover under proper land use management measures. However, land degradation is still continuing, and the industrialisation processes in this region have accelerated the degradation process. In the future, the government should determine the gap between the supposed policy effects and the real policy effects, from the policy-making process to the policy implementation process, covered by all grassland-related stakeholders, such as governments at all levels, decision-makers, and local herders. In addition, multi-ecological policies and long-term investment should be placed on the policy agenda.

Research Question 2: How can we identify drivers of land degradation and grassland degradation at the county level?

Chapter III explains the reasons for the occurrences described in Chapter II. In this chapter, the driver dynamics were analysed, compared and ranked at the county level to determine whether any statistical evidence can explain why ecological conditions in this region improved after 2000. A clustering approach, partial order theory and Hasse diagram techniques were implemented to compare and rank the drivers of land degradation at the county level. Furthermore, the causal relationships and key policy measures were summarised in this chapter.

The results of Chapter III showed that, before 2000, human disturbance was the dominant driver responsible for land degradation in eight out of the twelve counties in Xilingol, followed by urbanisation and water conditions. These results showed that livestock and the growing population were the major drivers that account for most degradation in Xilignol. During this period, the major policies for stimulating economic development included the “Economic Reform” and the “Household Production Responsibility System”. These policies led to an increase in population and livestock, which were the major drivers responsible for degradation up to 2000.

After 2000, the effects of human disturbance decreased, and was the responsible driver in only four counties; urbanisation was the major driver responsible for degradation in seven counties. In this period, two groups of policies that control the pressure of human disturbance and combat degradation were launched in this region. The results showed that human disturbance decreased significantly after 2000; the ecological protection policies had a direct impact on the human factor. The links between the individual mechanisms were also obvious after 2000: ecological protection policies restricted the number of livestock and moved users of degraded grassland led to urban expansion. Urban expansion causes all kinds of side effects such as road construction, road development resulting in grassland fragmentation, and even threatened biodiversity. Furthermore, restrictions in the number of livestock have led to the government and local people pursuing economic benefit by exploring the mining resources of Xilingol, which is rich in coal. Mining developments have destroyed grassland due to the excavation of the grassland surface. In addition, processes related to coal mining, such as the construction of roads and chemical factories, and the increased consumption of water resources, have led to surface water shrinkage and a drop in the groundwater table.

In this chapter, we identified drivers of land degradation in each period and analysed their dynamics in Xilingol. POR and HDT were implemented to compare and rank non-linear relationships between drivers and their effects at the county level. Since the county is the basic administrative unit in China, evaluating drivers at the county level is crucial for evaluating and adjusting current policy measures. This process enabled us to derive recommendations according to the dominant drivers in each county. The compared results were also useful for building scenarios to explore future developments.

<u>Research Question 3:</u> *How can we gain a better understanding of the relationship between drivers and grassland degradation?*

After identifying the dominant drivers for each county in both periods, Chapter IV looked at how each driver had affected grassland degradation, and what the effects (relationship) look like. It then simulated grassland dynamics on the basis of the elaborated non-linear relationships between drivers and grassland degradation at the pixel level.

A machine learning model, XGBoost, was implemented in this study, and SHapley Additive exPlanations (SHAP) values were then used to crack the black box model and visualise these complex relationships. The resulting model was used to map the primary drivers of grassland degradation in Xilingol, and the relevant hotspots. A predicted map was produced to identify high risks of further degradation in the future. The primary driver map for grassland degradation was produced to transform the non-linear relationship into understandable rules. The results showed how to build a machine learning model, which includes how to organise datasets and how to evaluate the model step by step. The four major drivers of grassland dynamics derived from the model were: the change in distance to dense grass, moderately dense grass or sparse grass, and sheep density. These were the drivers of grassland degradation. The visualised non-linear relationships revealed that areas at a greater distance from dense grass became degraded more easily, and vice versa for sparse grass. Moderately dense grass yielded more complicated results: the distance to moderately dense grass has both positive and negative effects on the grassland degradation process. The relationship between sheep density and grassland degradation was contrary to expectations. Furthermore, the high risk map showed that regions with a good quality of grassland have a high risk of degradation in the future, due mainly to local people relying on good-quality grassland and tending to overuse it. Against this background, regions with good-quality grassland should be given greater attention, taking into account the need for more suitable land planning.

In this chapter, a "state–of-the-art" machine learning model was used to simulate and predict grassland dynamics in Xilingol, which generated a robust model with a high degree of accuracy in this study. The most important step was to open the black box model and take a closer look at what the non-linear relationship looks like. The primary drivers of grassland degradation were mapped at the pixel level. We have enriched the methodology of simulating land use change and identifying major drivers.

2 Discussion and conclusions

The most important contribution of this thesis is to provide a comprehensive and systematic analysis of land use change and land degradation processes. Partial order theory was then used to compare and rank land degradation drivers at the county level, and the black box was cracked to visualise the complex relationship between drivers and grassland degradation. This thesis has improved the state of technology and methodology. The major conclusions can be summarised in the three aspects below.

1. Land activities were strong and land degradation was curbed after 2000, but still continued. The land use change process had obvious government-driven characteristics.

Chapter II provides a detailed analysis of land use and land cover changes and land degradation processes over space and time to determine what has happened and where the basic issue lies in the topic of land change. The dataset was generated by visual interpretation, a time-consuming activity. However, after validating by way of field experiment, it exhibited a high degree of accuracy. The datasets span a long period, from 1975 to 2015, covering five-year intervals. The results showed that land use and land cover have changed dramatically in Xilingol, and that ecological conditions improved after 2000. In a bid to discuss the root causes of land use/land cover change and land use change processes, a policy frame including policy-induced land use change before 2000 and policy responses to land degradation after 2000 was formulated. The results showed that the aim and implementation time of the policy match well with the land degradation process. Severe degraded ecological conditions drew considerable attention, and a set of policies were launched to recover the seriously degraded region.

However, degradation still continues. In addition, some ecological protection measures such as the double-edged sword did not improve the condition of grassland in Inner Mongolia, but led to a further degradation in the study region. Taking the example of the fencing policy, the aim of this measure was to protect severely degraded regions from human disturbance, such as grazing. However, previous research has determined that fencing has limited the mobility of livestock, leading to further degradation in Inner Mongolia (Xu *et al.*, 2015). Against this background, more ecological measures should be considered to increase the mobility of livestock and halt grassland degradation.

The results of Chapter II are line with a set of previous findings (Li *et al.*, 2012b; Tong *et al.*, 2017). However, there is rare research focus on reasons analysis of degradation. Due to limited data, driver dynamics had been missing before. In a bid to answer these question, the second issues were tackled in Chapter III.

2. The effects of human disturbance diminished, while rapid urbanisation/industrialisation increased after 2000; ecological protection policy is closely related to driver dynamics.

There was a need to analyse these causes at the county level, using a clustering approach before and after the year 2000. By then presenting these complex driver effects, greater understanding of these issues was gained. Against this background, we introduced the partial order theory (POR) and Hasse diagram techniques (HDT) to compare and rank major drivers of land degradation at the county level. In Chapter II, the relationship between drivers and land use change processes was clarified. In this chapter, the relationship between the policy frame and driver dynamics was determined. The ecological engineering projects controlled the pressure of human disturbance (relocation of the population and reduction in the number of livestock). However, this limited husbandry development and led the local government to explore more mining resources in Xilingol, which led to a new form of degradation, such as industrialisation degradation. It was ascertained that the causal relationship between policies, drivers and degradation processes is helpful for proposing new solutions that do not focus on symptoms alone.

After identifying the major drivers of land degradation for each county, there was an urgent need for better understanding of the environmental issues and their potential measures in Xilingol. This includes gaining an understanding of the effects of each driver, and taking a close look at these drivers' complex, non-linear relationship to degradation, as well as predicting degradation hotspots. Based on these findings, various land use models are primarily considered to address such issues. Chapter IV answered these issues.

3. The quality of grassland controlled the number of livestock, and good-quality grassland is at high risk of further degradation.

Interactions and relationships between the human system and the natural system are complicated and non-linear. Generally, in a bid to determine the key relationship or the major conflict between the two systems, scientists usually simplify the complex relationship or concentrate only on the key interaction. But the development of artificial intelligence leads to the emergence of more methods for understanding these complex relationships. First, what is the “complex relationship between drivers and land use change”? In this study, it is described as the influence of drivers that are either “negative or positive”. In this chapter, the machine learning method was used to explore such a complex relationship.

In this chapter, a non-linear model was found to achieve a better predictive quality than linear methods, but it also improved our understanding of how grassland degrades in the Xilingol League. Based on this, a map of potential grassland degradation and a map of the primary drivers of grassland degradation were produced. These results may help decision-makers and local herders to spatially identify the underlying drivers of grassland degradation and the hotspots of degradation.

In addition, more research must be done into land use change and the related drivers in Inner Mongolia. Popular methods, most of which are based on a linear assumption between drivers and land use change processes, are inadequate. A comprehensive, systematic understanding of land use change for land degradation, as well as the causal relationship between land use change and its drivers, is still missing. Two different methods (POR/HDT, XGBoost) were implemented to evaluate the drivers of land use change and identify its drivers. This study concludes that multiple methodologies should be used to develop integrative assessments of the evolution of the drivers of land use and land change in Inner Mongolia.

3 Limitations and outlook

Overall, this thesis provided a comprehensive understanding of land use and land cover change that led to land degradation, and clarified the causal relationships between drivers and land use change from the county scale to the pixel scale. Xilingol, as a typical region with grassland as the major type of land use, is the perfect example to represent the Mongolian Plateau when analysing its complicated human-environment system. In this thesis, two different methods were used to evaluate drivers of land use change and to simulate grassland dynamics across the whole region. The non-linear relationship between land use change and its drivers were revealed and high-risk grassland degradation identified. All data provided in this thesis are freely available on the internet; most are available for whole of

Inner Mongolia. The analysis in this thesis therefore has the potential for application to other regions. To conclude, the study highlights several limitations and possible follow-up research directions that are beyond this scope of this thesis.

First, the results are challenged by data limitations referring to data types, spatial extent and temporal resolution. More specifically, in Chapter III, driver data were collected at an aggregate level with on only nine drivers, three groups of which were used for comparison and ranking purposes. With regard to the identified major drivers of land degradation, the real situation of drivers of land degradation would be more complicated, and there would be a larger number of drivers. In Chapter IV, the spatial resolution of the ML model input data also limited the model results. As with livestock data, finer spatial resolution cannot be accessed in such a vast region, so we used statistical livestock data at an aggregated (county) level as input for the model, which may reflect more spatial details of grazing effects. For further research in the future, more drivers that stand for economic effects (e.g. the price of livestock and hay), indicators that stand for the effects of policy (e.g. government subsidies) and drivers that stand for improvements in techniques should be considered as the great potential that significantly affects processes of land use change.

Second, in Chapters II, III and IV, policy induced dramatic land use change processes, and serious ecological degradation resulted in ecological construction projects; also, the causal relationships between policies and possible drivers were elaborated normatively. Since 2000, various ecological policies and regulations have been introduced and have worked effectively on the Inner Mongolian Plateau (Han *et al.*, 2008; Jiang *et al.*, 2006; Li *et al.*, 2014a). However, the policies had both positive and negative effects on grassland quality and the number of livestock (Gao *et al.*, 2016; Jiang *et al.*, 2006). Likewise, previous studies also showed that political pressure increased vulnerability to climate hazards (Li *et al.*, 2017a). The effects of policies are confusing and highly uncertain (Zhang *et al.*, 2017). Against this background, more integrated methods should be implemented to analyse policy effects. The numerous policy effects should be measured separately; as well, policy offsets effects induced by economic and climate change should be placed on the policy analysis agenda. The call to use more methods to obtain a better understanding of the path of policy effects is crucial for the sustainable development of grassland around the world.

Third, the limitations of the ML model's specifications also challenge the model results. ML models were characterised by data driven and the black box. The study shows that the ML model can be used to understand the complex relationship without any input of expert knowledge. However, there is still inadequate information on how to use ML models to simulate and predict land use change (Ahmadlou *et al.*, 2016; Tayyebi, 2013; Tayyebi & Pijanowski, 2014). The driver inputs and sampling strategies, modelling running principles, could also challenge the model results. Collecting more reliable datasets on climate change, livestock data and mining developing data over different spatial resolutions would enable us to build a more accurate land use prediction model and to determine the most likely drivers that are responsible for land use change across the study area.

Generally, the ML model XGBoost, combined with SHAP values, worked effectively to provide understanding of the non-linear relationship between human-nature systems. Based on this, the XGBoost model can be used to analyse a complex relationship, and its application can then be extended to several different aspects. The first step is to build a scenario and couple it with traditional land use models. Based on the understanding of the relationship between causes and LUCC, it would be possible to understand the complex relationships between socio-economic development or policy targets and land use demand. Then land use demand can be predicted under different scenarios coupled with traditional models to relocate land use demand, enabling land use change to be predicted in the plausible future. Second, XGBoost can be used to understand the processes and complex competitions and interactions between the different types of land use when simulating land use change. Generally, land use neighbour effects or window technology were used to address such complex relationships between the different types of land use when simulating land use change. Third, integrating our model with other models, such as economic or climatic models, conventional land use change models, and ecosystem services trade-off models, increases our understanding of the causes and consequences of land use change. Fourth, it is recommended to simulate multiple land use types simultaneously. In our current study, we recognised the change in grassland degradation as a binary classification issue. However, a model that includes all types of land use (multiple classification issue) is necessary in the future; XGBoost should be used to simulate changes in multi land use types.

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Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Doktortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Batunacun
20 Jan, 2020